Transferability Ranking of Adversarial Examples

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Abstract

Adversarial examples can be used to maliciously and covertly change a model’s prediction. It is known that an adversarial example designed for one model can transfer to other models as well. This poses a major threat because it means that attackers can target systems in a blackbox manner.

In the domain of transferability, researchers have proposed ways to make attacks more transferable and to make models more robust to transferred examples. However, to the best of our knowledge, there are no works which propose a means for ranking the transferability of an adversarial example in the perspective of a blackbox attacker. This is an important task because an attacker is likely to use only a select set of examples, and therefore will want to select the samples which are most likely to transfer.

In this paper we suggest a method for ranking the transferability of adversarial examples without access to the victim’s model. To accomplish this, we define and estimate the expected transferability of a sample given limited information about the victim. We also explore practical scenarios: where the adversary can select the best sample to attack and where the adversary must use a specific sample but can choose different perturbations. Through our experiments, we found that our ranking method can increase an attacker’s success rate by up to 80% compared to the baseline (random selection without ranking).

Introduction

Neural networks are vulnerable to adversarial examples in which adversaries aim to change the prediction of a model $f$ on an input $x$ in a covert manner (Szegedy et al. 2014). The common form of this attack is where an adversarial example $x' = x + \delta$ is created such that $f(x + \delta) \neq f(x)$ where $||\delta|| < \epsilon$. In other words, the adversarial example changes the model’s prediction yet the $x'$ appears the same as $x$.

Many popular and powerful adversarial attacks (such as PGD (Madry et al. 2018) and CW (Carlini and Wagner 2017)) are whitebox attacks. This means that in order to use these algorithms to generate $x'$, the attacker must have access to the learnt model parameters in $f$ (i.e., the neural network’s weights). Although this may seem like a strong limitation for attackers, it has been shown that different neural networks can share the same vulnerabilities to an adversarial example (Szegedy et al. 2014; Tramèr et al. 2017). As such, an attacker can simply train a surrogate model $f'$ on a similar dataset (Zhou et al. 2020), attack $f'$ to generate $x'$, and then deploy $x'$ on the blackbox model $f$ knowing that there will be a decent probability of success. This attack is called a transfer attack (Papernot, McDaniel, and Goodfellow 2016). This type of attack has been found to be effective across models trained on different subsets of the data (Szegedy et al. 2014), across domains (Naseer et al. 2019) and across even between tasks (Xie et al. 2017).

In practice, an attacker will only use one or several adversarial examples in an attack and not an entire dataset. Therefore, the task of the attacker is to select the adversarial examples which are most likely to transfer to $f$, given little information about $f$ (illustrated in Fig. 1). Here, the attacker can either search for the best instance ($x_i \in D$ for $x'_i = x_i + \delta$) or for the best perturbation of a specific instance ($\delta_j$ for $x'_j = x_j + \delta_j$). To understand these cases, let’s consider two different scenarios: In the first scenario, an attacker is trying to evade detection of some anti-virus model $f$ by using a variant of some malware (represented as $x_i$) such that some modification to it ($\delta$) will make it perceived by $f$ as benign software (Mahdavifar and Ghorbani 2016).
In the second scenario, an attacker wants to tamper a specific patient’s medical image $x$ with some perturbation $\delta_j$ such that $x_j'$ will be falsely classified as containing some medical condition (Hirano, Minagi, and Takemoto 2021; Levy et al. 2022). Here ranking is done on potential perturbations because there is only one $x$. We note that in both cases, the attacker (1) has only one attempt to avoid being caught or (2) cannot get feedback from $f$, but must select the sample $x_i$ or perturbation $\delta_j$ which will most likely transfer to the victim’s model $f$.

To find the best $x_i$ or $\delta_j$ using surrogate $f'$, the attacker must rank potential adversarial examples accordingly to their expected attack success on $f$. We call this measure the expected transferability (ET). To the best of our knowledge, there are no works which propose a means for ranking adversarial examples according to their ET. Current works, such as (Tramèr et al. 2017; Dong et al. 2019; Zhu, Sun, and Li 2021), determine if $x'$ transfers by directly evaluating it on the victim’s model $f$. However, in a blackbox setting, an attacker cannot use $f$ to measure success. Therefore, this approach can only be used as an upper bound, but cannot be used to (1) help the attacker select the best adversarial example(s) or (2) measure a model’s robustness to transferability attacks given the attacker’s limitations.

In this paper, we explore the topic of ranking adversarial examples according to their ET. Our work offers several contributions: (1) we propose the concept of expected transferability and define the ranking problem for adversarial examples, (2) we suggest a way to approximate the ET of an adversarial example and a heuristical way to increase the accuracy and practicality of the method, (3) we introduce a new metric (“transferability at $k$”) to measure attack performance considering an attacker’s best efforts and (4) we frame the problem of transferability realistically in the perspective of a blackbox attacker: we propose the use of additional surrogates to evaluate transferability.

**Definitions**

In this section we introduce the concept of expected transferability, define the task of ranking an adversarial example’s transferability, and propose the metric “transferability at $k$”.

In this work, we assume a blackbox attack model, where the attacker has information about the victim’s model $f$ but does not have access to the trained weights of $f$ and cannot query $f$. Information about $f$ might include the distribution of the training dataset used to train $f$ ($\mathcal{D}_{train}$) and the architecture of $f$. We note that even if the attacker knows the victim’s architecture and training set, predicting transferability is still a challenging problem (Katzir and Elovici 2021).

**Expected Transferability (ET)**

Let $F$ be the set of all possible models scoped and based on the attacker’s knowledge of $f$ (i.e., $F$ is the set of all surrogate models that reflect $f$). In our setting, the attacker uses the surrogate model $f' \in F$ to create adversarial examples (denoted as the set $\mathcal{D}^*$).

We define the expected transferability of an adversarial example $x_i' \in \mathcal{D}^*$ as the probability that $x_i'$ will successfully transfer to a random model in $F$. A successful transfer of $x_i'$ to model $f_j \in F$ can be defined as the case where $f_j(x_i') \neq y_i$ for an untargeted attack and $f_j(x_i') = y_i$ for a targeted attack where $y_i$ is the ground truth label of $x_i$ and $y_t$ is the attacker’s target class.

It can be said that the attacker’s goal is to select a sample $x'$ which has the highest probability to transfer to random model drawn from the population $F$. For untargeted attacks, we can measure $x'$’s transferability with

$$S(x') = \mathbb{E}_{f \sim F}[f(x') \neq y]$$

(1)

$S$ can be used to rank adversarial examples because if $S(x'_i) > S(x'_j)$, then $x'_i$ is more likely to transfer to a random model in $F$ than $x'_j$. Note that (1) can similarly be defined for targeted attacks as well.

**Transferability Ranking**

Given $S$, the attacker can sort the potential adversarial examples according to their ET. Therefore, we define the task of transferability ranking as the problem of obtaining an ordered set of adversarial examples $\{x'_1, x'_2, ...\}$ such that $x'_i \in \mathcal{D}^*$ and $x'_i > x'_j$ if $S(x'_i) > S(x'_j)$.

Note that when applying $S(x')$, it is possible to measure the expected transferability rank different samples from a dataset $x' = x + \delta, x \in \mathcal{D}$ or different perturbations on a specific sample from the dataset $x' = x + \delta, x \in \mathcal{D}, \delta_j \in \delta$. Ranking adversarial examples by perturbation is relevant for attacks where multiple runs of the attack algorithm produce different perturbations (Madry et al. 2018).

**Transferability at $k$**

In a real-world attack, an attacker will curate a finite set of $k$ adversarial examples on $f'$ to use against $f$. To ensure success, it is critical that the attacker select the $k$ samples that have the highest ET scores.

The top $k$ samples of $\mathcal{D}^*$ are denoted as the set $S_k(\mathcal{D}^*)$ where setting $k = 1$ is equivalent to selecting the sample that is the most likely to transfer.

Identifying the top $k$ samples is not only useful for the attacker, but also the defender. This is because a defender can evaluate his or her model’s robustness to attacks given the attacker’s best efforts (attacks using the top $k$ samples). We call this performance measure the transferability at $k$ defined as

$$\frac{1}{k} \sum_{i=1}^{k} (f(x'_i) \neq y), x'_i \in S_k(\mathcal{D}^*)$$

(2)

where a similar form can be written for targeted attacks.

**Implementation**

In this section we propose methods for implementing $S$ and estimating the transferability at $k$ without access to $f$.

**Approximate Expected Transferability (AET)**

Although the set $F$ is potentially infinite, we can approximate it by sampling models from the population $F_0 \subset F$.
With $F_0$ we can approximate $S$ by computing
\begin{equation}
S(x') = \frac{1}{|F_0|} \sum_{j=1}^{|F_0|} (f_j(x') \neq y)
\end{equation}
for $f_j \in F_0$, and similarly for targeted attacks.

In summary, we propose the use of multiple surrogate models to estimate ET: one surrogate model is used to generate the adversarial example ($f' \in F$) and one or more surrogate models ($F_0 \subset F$) are used to estimate the transferability of the adversarial example to $f$.

### Heuristical Expected Transferability (HET)

Although we can use (3) to compute ET, the approach raises a technical challenge: it is impractical to train a significantly large set of surrogate models $F_0$. For example, training a single Resnet-50 on ImageNet can take up to 4 days (Wightman, Touvron, and Jegou 2021). However, if $|F_0|$ is too small then $S$ will suffer from a lack of granularity. This is because, according to (3), each model reports a 0 or 1 if the attack fails or succeeds. To exemplify the issue of granularity, consider a case where $|F_0| = 10$ and we set $k = 100$. If $D^*$ contains 1000 adversarial examples which fool all 10 models, then all 1000 samples will receive a score of 1.0. However, the true $S$ of these samples vary with respect to $F$. As a result, we will be selecting $k = 100$ random samples randomly from these 1000 which is not ideal.

To mitigate this issue, we propose using continuous values to capture attack success for $x'$ on each model. Specifically, for each model, we use the model’s confidence for the input sample’s ground-truth class. This value implicitly captures how successful $x'$ is at changing the model’s prediction since lower values indicate a higher likelihood that $x'$ will not be classified correctly (Goodfellow, Shlens, and Szegedy 2015; Madry et al. 2018). When averaged across $|F_0|$ models, we can obtain a smoother probability which generalizes better to the population $F$. Averaging model confidences is a popular ensemble technique used to join the prediction of multiple classifiers together (Ju, Bibaut, and van der Laan 2018). However, here we use it to identify the degree in which a sample $x'$ exploits a set of models together.

To implement this heuristic approach, we modify (3) to
\begin{equation}
S(x') = \frac{1}{|F_0|} \sum_{j=1}^{|F_0|} (1 - \sigma_i(y(f_j(x')))), f_j \in F_0
\end{equation}
where $\sigma_i(y)$ returns the Softmax value of the logit corresponding to the ground-truth label $y$.

We demonstrate the benefit of using HET (4) over AET (3) with a simple experiment: We take a Resnet-50 architecture for both $f$ and $f'$, trained on the same ImageNet train set (Deng et al. 2009). Then, we create $D^*$ by attacking the ImageNet test set with PGD ($\epsilon = 25$). Finally, we compute the AET and HET on each sample in $D^*$ with $|F_0| = 3$ surrogates.\(^1\) In Fig. 2, we plot the attack success rate of $D^*$ on $f$ for different $k$ when sorting the samples according to AET and HET respectively. We observe that (1) although $D^*$ has a 98% attack success rate on $f'$, it only has a success rate of 20% on $f$ even though both $f$ and $f'$ are identical in design, and (2) HET performs better than AET, especially for lower $k$ (i.e., when we select the top ranked samples).

### Blackbox Ranking Strategies

As discussed earlier, it is more likely that an attacker will measure a sample’s transference using surrogates and not the victim model $f$ (as done in previous works). Below, we propose three strategies/procedures for applying ET to rank the transferability of a sample $x'$ without using $f$ (illustrated in Fig. 3):

#### Without ET.
This is the naive approach where the attacker uses one surrogate model ($f'$) to select the adversarial examples. There are a few ways of doing this. For example, the attacker can check if $x'$ successfully fools $f'$ and then assume that it will also work on $f$ because $f \in F$. Another way is to evaluate the confidence of $f'$ ($\sigma_i$) on the clean sample $x$ to identify an $x$ which will be easy to attack (Özbulação et al. 2021; Zhu, Sun, and Li 2021). Although this strategy is efficient, it does not generalize well to $F$. Even in a blackbox setting, where the attacker knows the victim’s architecture and training set, a sample $x'$ made on $f'$ will not necessarily work on $f$. This is because even a model’s random initialization has a significant impact on transferability (Katzir and Elovici 2021).

#### With HET. In this strategy, the attacker utilizes multiple surrogate models ($F_0$) to approximate the expected transference of $x'$ to $f$, as expressed in (4). Here, the performance depends more on the attacker’s knowledge of $f$ (the variability of $F$) but less so on the random artifacts caused by initialization of weights and the training data used.\(^2\) This is because the averaging mitigates cases where there are only a few outlier models in $F_0$ which are vulnerable to $x'$. As a result, the final transferability score captures how well $x'$ transfers to vulnerabilities which are common among the models in $F_0$. The concept of models having shared vulnerabilities has been shown in works such as (Wang et al. 2020; Nakkiran 2019).

#### With HET and Transforms.
To increase robustness, the definition of ET in (1) can be extended to include any potential transformations on the inputs of $f$. For example,

\[^1\]Note: $f$ is never included in $F_0$ for all of our experiments.

\[^2\]This assumes that the training data for each model in $F$ is drawn from the same distribution.
some common transformations on visual inputs include image resizing, image compression, image cropping, and even potential defences (Tramer et al. 2020; Levy et al. 2022). To implement this strategy, the attacker applies random potential transformations to $x'$ prior to evaluating it on $[F_0]$.

**Experiment Setup**

In this section we detail the experiments which we have performed to evaluate the proposed blackbox ranking strategies.

**Parameters**

**Evaluation Measures.** To evaluate our ranking methods, we use transferability at $k$ as defined in (2). Note that transferability at $k$ can also be viewed as the attack success rate on $f$ for the top-$k$ recommended samples. We remind the reader that our ranking is performed without access to $f$. Thus, the attack success rate captures the transferability of the $k$ samples from $f'$ to $f$.

**Datasets.** For our experiments, we used the popular CIFAR10 (Krizhevsky, Hinton et al. 2009) and Imagenet (Deng et al. 2009) benchmark datasets. The predefined training sets were used to train $f'$ and $f''$ and the predefined test sets were used to create the adversarial examples ($\mathcal{D}^*$). Since $f(x) \neq y$ is counted as a successful attack, we must remove all samples from the test set where the clean sample is misclassified. This is done in order to avoid bias and focus our results strictly on samples which transfer as a result of the attack. In total, we used 9426 samples in CIFAR10 and 37729 samples in Imagenet.

**Models.** In experiments which used the CIFAR10 dataset, we trained our own ResNet-18 models. For experiments which used the ImageNet dataset, we used 10 trained ResNet-50 models from Kaplun et al. (2022) where all models were trained in the same way except for their initial weights which were random. For all of our experiments, we designated one model as $f'$ and three models as $F_0$. To capture the performance across multiple victim models, we considered the average transferability at $k$ over multiple victim models as $f$ (i.e., 8 and 6 for CIFAR10 and Imagenet experiments respectively). In our experiments, $f$, $f'$, and $F_0$ use the same model architecture unless stated otherwise.

**Attack Algorithms.** For the attacks, we use FGSM and several variations of PGD. Both of these algorithms are considered accepted baselines when evaluating adversarial attacks (Goodfellow, Shlens, and Szegedy 2015; Croce and Hein 2020; Tramer et al. 2020). The FGSM attack performs a single optimization step on $x$ to generate $\delta$ (Goodfellow, Shlens, and Szegedy 2015). The PGD algorithm performs multiple iterations where each iteration normalizes $\delta$ according to a given $p$-norm (Madry et al. 2018).

We also consider two variations of PGD which were shown to increase transferability: (1) ‘PGD + momentum’ which uses momentum in the optimisation process (Dong et al. 2018) and (2) ‘PGD + Input diversity’ which applies transformations during the optimisation process to increase transferability (Xie et al. 2019).

In our experiments, we only perform untargeted attacks ($f(x') \neq y$), where the algorithm is executed on $f'$ alone (bounded by $\epsilon = \frac{1}{255}$ for CIFAR10 and $\epsilon = \frac{4}{255}$ Imagenet). In our experiments, we used only PGD unless explicitly stated otherwise.

**Ranking Algorithms.** We evaluate our three ranking strategies for the blackbox setting: (1) Without ET, (2) With HET and (3) With HET and Transforms. For the ‘Without ET’ strategy, we evaluate two implementations:

**w/o ET-SM** In this implementation of the strategy we score a sample’s transferability by taking $1 - \sigma_i(f'(x))$ where $x$ is the clean sample. The use of Softmax here is inspired from the works of ¨Ozbulak et al. (2021) where Softmax is used to capture a model’s instability in $f$ (not $f'$).

**w/o ET-Noise** For this version we follow the work of Zhu, Sun, and Li (2021). In their work the authors found that samples which are sensitive to noise on the victim model $f$ happen to transfer better from $f'$ to $f$. We extend their work to the task of ranking: each clean sample in the test set is scored according to how much random noise impacts the confidence of the surrogate $f'$. Samples which are more sensitive are ranked higher. Similar to Zhu, Sun, and Li (2021), we also use Gaussian noise and set $\text{std}=\frac{16}{255}$.

Ranking with these strategies is achieved by (1) computing the respective score on each adversarial example $x' \in \mathcal{D}^*$ and then (2) sorting the samples by their score (descending order).

As a baseline evaluation, we select $k$ samples at random from $\mathcal{D}^*$ (no ranking). Note that this is essentially the same as the common transferability evaluation measure used in literature, which is to calculate the average success rate. This baseline can also be viewed as a kind of lower-bound on performance.

Finally, we contrast the above ranking methods to the performance of the optimal solution (upper-bound). In the task transferability ranking (blackbox), the optimal solution achieved by ordering the samples according to their performance on $f$ (as opposed to using surrogates).
Environment & Reproducibility. Our code was written using Pytorch and all models were trained and executed on Nvidia 3090RTX GPUs. To reproduce our results, the reader can access our code online.3

Experiments
We investigated the following attack scenarios: (Sample Ranking) where the attacker must select the top \( k \) samples from \( D \) to use in an attack on \( f \), and (Perturbation Ranking) where the attacker must select the best perturbation for a specific sample \( x \) in an attack on \( f \). In the sample ranking scenario we set \( k = \{5, \ldots, |D^*|\} \) and for the perturbation ranking scenario we set \( k = 1 \).

E1. Sample Ranking Scenario. We performed four experiments with this scenario:

E1.1 - General Performance. In this experiment we compare the ranking methods without any transforms applied to the inputs of \( f \). This is a common assumption taken in transferability works.

E1.2 - Transformations. Here we analyze the impact on the methods’ performance when the victim applies transforms to the inputs of \( f \): image resizing and Jpeg compression. For resizing we lowered and then returned the images’ resolution using interpolation (3% for CIFAR10 and 12% for ImageNet). Image resizing and Jpeg compression are common transforms applied prior executing models (Hashemi 2020).

E1.3 - Attack Algorithms. For this experiment, we compare how the different ranking methods perform when using different attack algorithms.

E1.4 - Model Architectures. In many cases, the attacker does not know the victim’s model architecture and may use a different architecture for the surrogates than what is used in \( f \). In this experiment, we evaluate this case by having the attacker use ResNet-18 architecture while the victim uses the wideResNet architecture (Zagoruyko and Komodakis 2016).

E2. Perturbation Ranking Scenario. We performed two experiments with this scenario:

E2.1 - General Performance. Given a sample \( x \) we generated 5 perturbations using the PGD algorithm on \( f' \). The ranking methods were then used to select the best adversarial example to use. This experiment was repeated for every sample in the test set, and the average performance was taken.

E2.2 - Transformations & Architectures. In this experiment, we apply the resize and compression transforms on all inputs to \( f \) and also evaluate transferability to unknown architectures. However, here we evaluate the methods’ ability to rank perturbations.

Experiment Results
E1. Sample Ranking

E1.1 - General Performance. In Fig. 4 we plot the transferability at \( k \) of the three proposed ranking strategies and the two baselines for increasing sizes of \( k \). The figure shows that ranking significantly increases the attack success rate for all \( k \) compared to not using ranking at all (random). This affirms that the concept of transferability ranking, defined in this work, can indeed be beneficial to attackers (and to defenders seeking to evaluate their model’s robustness).

These results also have serious implications. For example, in the case of ImageNet ResNet-50, without transferability ranking a blackbox attacker has only a 20% chance of success. However, with transferability ranking, the attacker is nearly guaranteed success when using a small \( k \). This is interesting considering that the ImageNet ResNet-50 model is more complex than the CIFAR10 ResNet-18 model, yet the gain of using transferability ranking is significantly larger.

Among the ranking algorithms, we can see that the most effective ranking strategy is to use HET. For both models, HET performs very similar to the upper-bound. We also note that using \( F_0 \) (with HET) can increase the transferability at \( k \) by more than 10% on average compared to just using \( f' \) (without ET).
Finally, we can see that the concept of ‘no free lunch’ may apply to transferability ranking methods since ‘w/o ET - Noise’ sometimes exceeds the performance of other methods for certain ranges of $k$. Therefore, an attacker may want to use a specific method depending on the required $k$ or possibly change other parameters such as the attack algorithm being used.

**E1.2 - Transformations.** In Fig. 5 we present the transferability at $k$ in the presence of transforms. We can see that these transforms significantly hinder the ranking methods’ ability to predict transferability. This is especially apparent for the CIFAR10 ResNet-18 model where the error bars show that the variability between victim models increased. Regardless, all of the ranking strategies still outperform the baseline. Moreover, if the attacker knows which transforms are being used, then it is possible to achieve near optimal results (with HET & Transformations).

In this experiment we see some different patterns between the CIFAR10 and Imagenet datasets. The ranking strategies that were not performed on the transformed example (all but with HET) show mixed results on the CIFAR10 dataset but show a clear distinction in the Imagenet dataset. This further implies that when choosing a ranking strategy, some methods may be better on one dataset but worse in another.

**E1.3 - Attack Algorithms.** In Table 1 we present the transferability at $k$ for different attack algorithms when applied to CIFAR10 ResNet-18 models. Interestingly, the ranking methods significantly increase the transferability of the FGSM attack from 0.56 to 0.95 when $k$ is set to the 80-th percentile. Moreover, it appears that using HET provides can provide near optimal results for large $k$ regardless of the algorithm used. These results also suggest that the problem of choosing an attack algorithm is orthogonal to the problem of ranking adversarial transferability. We leave this investigation to future work.

**E1.4 - Model Architectures.** In Table 2 we present the ranking performance in a stronger blackbox scenario: where the attacker does not know the the victim’s model architecture. Although the baseline performance is initially high, we can see that the ranking methods still raise the performance significantly higher, even for very large $k$. Moreover, for small $k$, the ranking methods are able to select samples which are guaranteed to transfer to the unknown model.

**Summary.** Overall, the results for this scenario show that an attacker can significantly increase the chances of successfully performing a transfer attack if one of the proposed ranking strategies are employed -especially HET. Moreover, the experiments have demonstrated that attackers who only need to perform a few attacks (e.g., trick financial models) can actually increase their likelihood of success by using transferability ranking -even if the attacker is highly limited in the knowledge of the victim.

As for evaluating transferability, we suggest that researchers and engineers use transferability at $k$ as a means for more accurately assessing their model’s robustness to transfer attacks. This is because the results show that attackers which use small $k$ are likely to identify transferable samples. As future work, it would be interesting to investigate the performance of ranked adversarial examples in the presence of defences, and to better analyse what makes the top $k$ samples so transferable.

### E2. Perturbation ranking

**E2.1 - General Performance.** In table 3 we present the results from the perturbation ranking experiments on the CIFAR10 ResNet-18 models. Under the column ‘Natural’ the average transferability at $k = 1$ for every sample in $D^+$ is provided. Even though only five perturbations are offered per sample $x$, the ranking methods are still able to increase the transferability rate by 3%-8%.

**E2.1 - Transforms & Architectures.** Unlike the sample selection scenario, here the performance of HET is similar to the strategies without HET. We believe that this might be because some images have stronger artifacts than others which interferes with any potential perturbations that are generates on the clean version. For example a blank image will undergo stronger Jpeg compression than a busy image. Regardless, we found that the task of adversarial ranking of perturbations is challenging in the presence of transforms unless knowledge of the transforms are available (with HET & Transforms).

Finally, we found that the proposed ranking strategies work very well when the victim uses a different architectures. Moreover, just like in the sample ranking scenario, applying transforms improves the method’s ability to transfer to unknown architectures (not captured by $|F_0|$).

### Related Work

There has been a great amount of research done on adversarial transferability, discussing attacks (Naseer et al. 2019; Wang et al. 2021; Springer, Mitchell, and Kenyon 2021; Zhu, Sun, and Li 2021), defences (Guo et al. 2018; Madry et al. 2018) and performing general analysis of the phenomena (Tramèr et al. 2017; Katzir and Elovici 2021; Demontis 2022).
In this paper we proposed the concept of expected transferability (ET) which enables us to define the task of transferability ranking. We propose ways to approximate the ET of adversarial examples in a blackbox setting and propose a new evaluation metric \( \text{transferability at } k \) to measure transferability in a more grounded manner than prior works. Our paper took into account the realistic perspective of a blackbox attacker and demonstrated that, with ranking, blackbox transfer attacks are far more threatening than previously perceived. By ranking adversarial examples, an attacker can change the likelihood of success from 20\% to nearly 100\% in some scenarios. Finally, of the proposed strategies for obtaining ranking scores, the heuristical expected transferability score \( \text{HET} \) was the most successful and robust. We encourage the use of \( \text{transferability at } k \) as a measure for evaluating a model’s robustness to blackbox transfer attacks to better capture a real-world setting.

### Conclusion

In this paper we proposed:

1. The concept of expected transferability (ET) to define the task of transferability ranking.
2. A new evaluation metric \( \text{transferability at } k \).
3. Propose ways to approximate ET in blackbox settings.
4. Demonstrate that ET offers a more realistic perspective compared to prior works.
5. Identify \( \text{HET} \) as the most effective and robust strategy.

These strategies provide a more grounded approach for evaluating model security in transfer settings, offering a clearer and more practical understanding of adversarial threat levels.
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