Natural and Adversarial Error Detection using Invariance to Image Transformations

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Abstract

We propose an approach to distinguish between correct and incorrect image classifications. Our approach can detect misclassifications which either occur \textit{unintentionally} (“natural errors”), or due to \textit{intentional adversarial attacks} (“adversarial errors”), both in a single unified framework. Our approach is based on the observation that correctly classified images tend to exhibit robust and consistent classifications under certain image transformations (e.g., horizontal flip, small image translation, etc.). In contrast, incorrectly classified images (whether due to adversarial errors or natural errors) tend to exhibit large variations in classification results under such transformations. Our approach does not require any modifications or retraining of the classifier, hence can be applied to any pre-trained classifier. We further use state of the art targeted adversarial attacks to demonstrate that even when the adversary has full knowledge of our method, the adversarial distortion needed for bypassing our detector is \textit{no longer imperceptible to the human eye}. Our approach obtains state-of-the-art results compared to previous adversarial detection methods, surpassing them by a large margin.

1. Introduction

Despite recent progress, state of the art recognition methods still have non-negligible error rates. For instance, typical top-5 error rate of modern classifiers on ImageNet is on the order of 4-5\% (Szegedy et al., 2016; Huang et al., 2017). As deep learning methods become incorporated into sensitive applications in medical, transportation, and security domains, dealing with remaining recognition errors becomes critical. The concern is aggravated by the discovery of \textit{adversarial attacks} on CNN-based recognizers, whereby errors in CNNs can be triggered on demand (Szegedy et al., 2013; Nguyen et al., 2015; Madry et al., 2017; Carlini & Wagner, 2017b). Such attacks have been shown to be capable of reducing accuracy of classifiers to arbitrarily low levels. Alarmingly, while images resulting from these attacks manage to fool state of the art classifiers, they appear indistinguishable, to the naked eye, from “normal” images classified correctly.

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![Image](image-url)
Traditionally, such adversarial errors and unintentional errors ("natural errors") have been treated as two separate problems. The former have motivated a sequence of defense mechanisms, each in turn defeated by subsequent modification of the attacks. The natural errors are simply considered a fact of life, and the main avenue to deal with them has been to improve classifier accuracy.

**Adversarial errors** Adversarial attacks are usually categorized as black box, when the attacker has no knowledge of the classifier parameters (weights), and white box, in which the attacker has full knowledge of the classifier. We use additional terminology to describe the level of knowledge the (white box) attacker has on the error detector itself: “known detector” (KD) attackers have full knowledge of both the classifier and the detector, while “unknown detector” (UD) attackers know only the classifier, and do not have any knowledge of the detector.

Additionally, one can characterize the “strength” of an attack by the degree of distortion it applies to the original image in order to “fool” the classifier (and the detector, if relevant). The higher the distortion the more perceptible it becomes, making it less likely to go unnoticed by a human, thus forming a weaker (and arguably less interesting) attack.

The rapidly expanding literature on the topic follows a "cat and mouse" competition between attacks and detection/defense. Almost all of the recently proposed detection methods have been evaluated in (Carlini & Wagner, 2017a), who used their strong C&W attack (proposed in 2017) to attack MNIST and CIFAR-10 classifiers. They found most methods exhibit good detection performance under the UD scenario but are easily defeated in the KD case. They further pointed out the weakness of using (deep) learning to construct adversarial error detectors as in (Gong et al., 2017; Grosse et al., 2017; Metzen et al., 2017)): “the least effective schemes used another neural network […] since […] given that adversarial examples can fool a single classifier, it makes sense that adversarial examples can fool a classifier and detector.” Other bypassed methods applied PCA on the images or network activations (Bhagoji et al., 2017; Hendrycks & Gimpel, 2016; Li & Li, 2017), or employed other statistical tests (Feinman et al., 2017; Grosse et al., 2017).

Only the Dropout method of (Feinman et al., 2017) forced the attacker to use a somewhat perceptible image distortion in order to bypass the detection, and only for the MNIST case. In the CIFAR10 case it was bypassed with an imperceptible distortion.

**Natural error detection** The dropout method was also applied in earlier work for natural error detection (Mandelbaum & Weinshall, 2017). An even simpler approach (Hendrycks & Gimpel, 2016) suggests to threshold the Maximal Softmax Response (MSR) in order to detect natural errors.

We propose a unified framework to detect classification errors, whether natural or adversarial. The key idea in our approach stems from our observation that robustness of classifiers’ outputs under certain simple image transformations (e.g. horizontal flip) is systematically different for cases of correct classification vs. cases of misclassification. This idea is schematically illustrated in Fig. 1.

We measure the KL-divergence between the outputs of the classifier under image transformations. Fig. 2 presents examples and histograms of this divergence score $D_{KL}$ for the cases of correct, naturally incorrect and maliciously misclassified images. (a) Examples of correctly classified (green), adversarially misclassified (blue) and naturally misclassified (red) ImageNet images. Corresponding detection scores $D_{KL}$ and predicted classes (using ResNet Inception V2) appear below each image. Other methods applied PCA on the images or network activations (Bhagoji et al., 2017; Hendrycks & Gimpel, 2016; Li & Li, 2017), or employed other statistical tests (Feinman et al., 2017; Grosse et al., 2017).

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incorrect image classifications. It shows we can use this divergence score $\mathcal{D}_{KL}$ to detect classification errors, whether natural or adversarial (see details in Sec. 2). This detection score can then provide a robust reject option for classifiers, and a degree of defense against adversarial attacks.

We show that our detector is hard for an adversary to defeat, even when the adversary has full knowledge of the detector’s process. We conjecture that this is partially due to the detector’s simplicity. For natural errors detection alone, we further propose to incorporate a learned Multi Layer Perceptron (MLP) for enhanced detection performance, as we can afford to use a more sophisticated detector in that case.

Our contributions can be summarized as follows:

1. We propose a unified framework for detecting classification errors (whether natural or adversarial).
2. We introduce a mechanism for inferring confidence in the classification of an image from its robustness under image transformations.
3. Our detector’s performance significantly improves over previous SOTA methods for detecting natural and adversarial errors (both targeted and untargeted).
4. We show that, unlike any previous method, SOTA targeted attacks, even with full knowledge of the detector, are forced to use perceptible distortion in order to bypass detection.
5. Our method can be applied to any pre-trained classifier, without any modifications or retraining. We demonstrate its superior performance, even when applied to classifiers that were fine-tuned to improve performance of competing natural error detection methods.

We will make our code available soon.

2. Detecting Classification Errors

A common goal in building visual classifiers is that classification output be robust under certain image transformations applied to the image. We observe that while this is generally the case for correctly classified images, this tends not to be true for misclassified ones. This relationship between the correctness of a prediction and its invariance under image transformations is the key to our approach.

We will restrict our attention to image transformations that can be expected to occur naturally in realistic imaging conditions, without affecting the content of the image. While we cannot provide a principled definition of the space of all such "natural" transformations, we can recognize such transformations intuitively. For instance, horizontal (left-to-right) flip is natural due to lateral symmetries in the world; zooming into the image is natural since it corresponds to bringing the camera closer to the scene; etc.

**Notation** An $N$-way classifier $F$ computes for an input $x$ an $N$-dimensional vector of class logits $Z(x) = [Z_1(x), \ldots, Z_N(x)]$. Using the softmax transformation, the logits can be converted to estimated posterior distribution over classes $F(x)$:

$$ F_c(x) = \frac{\exp Z_c(x)/T}{\sum_{c \in [N]} \exp Z_c(x)/T}, $$

where $F_c(x)$ is the estimated conditional probability of $c \in [N]$ being the class of $x$. $T$ is a temperature parameter (default is $T = 1$) affecting the resulting distribution’s entropy, that rises with $T$ (approaching uniform distribution as $T \to \infty$) and a delta function when $T \to 0$.

A classifier prediction is made by selecting $\hat{c}(x) = \arg \max_c F_c(x)$. This is an error on example $x$ with label $y$ if $\hat{c}(x) \neq y$.

Given an image transformation $t$, we can assess the degree of invariance of the classifier’s output under this transformation as the difference between two distributions, $F(x)$ and $F(t(x))$. As an illustration, Fig. 1 presents three images, along with their transformed ($t$=horizontal flip) versions. The right hand side shows the corresponding softmax outputs for both image versions. Note that for the correctly classified image (top row) the output is consistent across image versions, while for the misclassified ones (middle and bottom rows) the transformation induces significant
changes in the classifier’s output. It is immaterial for this figure which class indices in the plots correspond to the correct classes; what we are looking for is the difference between the $F(x)$ (black) and $F(t(x))$ (blue).

We convert this intuition into a concrete error detector by measuring the Kullback-Leibler Divergence\(^1\) ($D_{KL}$) (Kullback, 1959) between the two softmax outputs $D_{KL}(F(x)||F(t(x)))$ as a detection score. Figure 2b presents histograms of $D_{KL}$ scores (for $t =$ hor. flip) corresponding to three types of classifications: correct (green), naturally incorrect (red) and adversarially incorrect (blue) classifications of ImageNet images. Adversarial images were created using the strong C&W targeted attack on a pretrained Inception ResNet V2 classifier (Szegedy et al., 2016). Note that $D_{KL}$ scores exhibit fairly good separation between adversarially (blue) and naturally (red) misclassified images, and even better separation between adversarially misclassified and correctly classified (green) images.

The higher $D_{KL}$ is, the less stable the output of $F$ is on $x$ under transformation $t$, and so, the less confident we are that $F(x)$ is correct. A binary error detector is obtained by introducing a threshold $\tau$: if $D_{KL}(F(x)||F(t(x))) > \tau$, reject $x$ as a misclassified image.

In Section 4 we report on our evaluation of this simple algorithm on the tasks of detecting targeted and untargeted adversarial images, generated by state of the art attack methods. We found our approach to outperform previous adversarial detection methods by a large margin. Moreover, for the case of targeted “known detector” (KD) threat model, we found that it forest the attacker to induce a very high and visible image distortion in order to bypass our detector.

We note that image transformations have also been explored as a defense mechanism by (Guo et al., 2018), but in a totally different way. In particular, they did not explore the divergence between classifier outputs under different transformations. In a recent work, Tian et al. (2018) proposed to exploit the sensitivity of classification to image transformations for adversarial detection. But unlike our work their detection relies on a trained neural network, which can be easily bypassed in a KD scenario (Carlini & Wagner, 2017a). Moreover, they only demonstrate their method against targeted attacks on MNIST and CIFAR10 (and only for a single threshold setting).

3. Improving Natural Error Detection

The simplicity of $D_{KL}$ score is a virtue from a security standpoint, since the lack of a complex parametric mechanism makes it harder for an adversary to circumvent it (Carlini & Wagner, 2017a) in the worst case KD scenario. This is indeed supported by our experiments (Sec. 4) and by Fig. 2b: It indicates that the $D_{KL}$ score, based on a single transformation, suffices for detecting adversarial images.

However, Fig. 2b also implies $D_{KL}$ is less effective in separating natural errors (red) from correct classifications (green). This is partially due to the coarse binning hiding finer separation for very low values of $D_{KL}$, but our experiments confirm that the separation is indeed less significant than for adversarial images. However, if we restrict our attention to natural errors, we can afford to employ a more complex detection mechanism to enhance detection performance (since there is no adversary to exploit “loopholes” in it). Below we propose such a mechanism that captures the rich information contained in logits corresponding to different transformations. Here we consider a set of image transformation $\{t_1, \ldots, t_m\}$ rather than just one.

We create a new representation for $x$ that reflects the invariance of $F$ under these transformations, as follows (illustrated in Figure 3). Recall that $Z(x)$ is the vector of logit values computed by $F$ on $x$.

1. We jointly reorder logits vectors corresponding to the transformed image versions $\{Z(t_j(x))\}_{j=1}^m$. The sorted logit order is the same for all transformed versions of the input image, and is determined by the sorting (in descending order) of the logit values of the original input, $Z(x)$. This makes the representation independent of the predicted class $\hat{c}(x)$.

2. We truncate each reordered logits vector to $N' \leq N$ elements. We empirically found it reduces the detector’s overfitting.

3. We concatenate the reordered, truncated vectors into a single vector of length $(m + 1) \cdot N'$.

We then use a binary Multi Layer Perceptron (MLP) to predict the probability of the classification $F(x)$ being incorrect. To train it, we collect a set of category-labeled examples $(x_i, y_i)$ (ideally from a heldout set outside of $F$’s training data, and for each $x_i$ compute the logits vectors corresponding to the original input $Z(x_i)$ and its transformed versions $\{Z(t_j(x_i))\}_{j=1}^m$. These logits constitute the MLP’s input. We then assign this input with its corresponding error label $\epsilon_j$, set to 1 if $y_i \neq F(x_i)$ and -1 otherwise. See Section 4 for details on architecture and training of the MLP.

Note that in a scenario involving both natural and adversarial images, we could theoretically start by rejecting adversarial images using our simple $D_{KL}$-based mechanism. Then, assuming our detector is no longer susceptible to adversarial attacks, we could proceed to use this logits-based MLP for enhanced natural error detection. However, this mode
of operation may introduce additional vulnerabilities, for instance adversary fooling the MLP detector into rejecting correctly classified images as erroneous.

**Relation to data augmentation** Image transformations are commonly employed for augmenting the training set of a classifier. This may raise a question: how can we benefit from invariance to a transformation if the classifier, ostensibly, is trained to be invariant to it? A key observation here is that data augmentation does not necessarily force the classifier to learn *invariance* to transformations of a given image - the classifier may simply learn that the different transformed versions correspond to different *instantiations* of the same class, encouraging each one separately to output the correct class. In contrast, our method infers confidence in a prediction from actual invariance of classifiers’ outputs on transformed versions of an image. In fact, results in Fig. 2b were obtained using the horizontal flip transformation, for classifiers that included horizontal flip in their data augmentation procedure during training. Moreover, comparing our method’s performance on two CIFAR10 classifiers trained with vs. without horizontal flip augmentation showed no meaningful difference in our ability to reject errors. This suggests our method’s performance is independent of the classifier’s training data augmentation procedure.

4. Experiments

We evaluate our error detection method using four data-sets: CIFAR-10 (Krizhevsky & Hinton, 2009), STL-10 (Coates et al., 2011), CIFAR-100 (Krizhevsky & Hinton, 2009), and ImageNet (Russakovsky et al., 2015), which vary in terms of both number of examples and the number of classes. This is to confirm that the proposed method generalizes across task sizes. We demonstrate results with different classifiers, including CIFAR10 classifiers from (Carlini & Wagner, 2017b) and (Carlini & Wagner, 2017a), classifiers trained by (Mandelbaum & Weinshall, 2017) and the competitive Inception-ResNet-V2 classifier (Szegedy et al., 2016).

We employ the Receiver Operating Characteristic (ROC) curve and the corresponding Area Under ROC Curve (AUROC) to allow thorough evaluation of various detection policies (e.g., low mis-detection, low false-detection).

![Figure 3. Overview of (optional) learned detector. Given an image x and a pre-trained classifier F, we feed x and several (three, in this example) natural transformations of it into F. We jointly re-order all resulting logits vectors so that the logits vector for x (the original image) is in descending order, then truncate the logits vectors to retain only the N’ first logits and finally concatenate them to yield the input to our detector.](image)

![Figure 4. “Unknown detector” (UD) threat model. ROC curves corresponding to detecting targeted (solid line) and untargeted (dashed line) C&W attacks on ImageNet (Russakovsky et al., 2015) images (using the same classifier as in Fig. 2b). The L2 norms in the legend indicate the average (per pixel) norm of the perturbation produced by the attacker; pixels are in [0,255] range. Values in legend correspond to the AUROC (Area Under ROC) of the different methods. We use our method (red) with \( t = \) hor. flip and compare it to the dropout (blue) and MSR (green) methods. Increasing the attack’s confidence parameter from \( k = 0 \) (left) to \( k = 8 \) (right) hardly affects the adversarial noise norm \((L_2)\), but significantly impairs performance of both competing methods. In contrast, our method still achieves AUROC≈1, indicating nearly perfect detection.](image)
using a horizontal flip transformation.

We run both targeted and untargeted attacks (in the targeted case we randomly assign target labels). We find our method ranks best in all comparisons, nearing perfect detection capabilities (AUROC ≈ 1).

The C&W attack employed in these experiment has a tunable parameter “confidence” $k$ that determines how confidently should classifier $F$ misclassify the resulting adversarial image. Higher values lead to more confidently misclassified examples with better transferability across classifiers (Carlini & Wagner, 2017b), at the cost of increased image distortion (quantified here using the $L_2$ norm). The experiments in Fig. 4 were conducted using either the minimum attack confidence value $k = 0$ (left) or a slightly higher one, $k = 8$ (right). Note that despite the imperceptible increase in image distortion, the advantage of our method becomes even clearer in the higher confidence case (right). We see the same phenomenon on CIFAR10 (using the classifier from (Carlini & Wagner, 2017a)). Fig. 5 depicts the resulting AUROC vs. average image distortion norm (controlled indirectly by varying confidence $k$ of the attacker) for the targeted (left) and untargeted (right) attacks. It shows our method can detect highly confident, transferable, adversarial images well after the competing methods drop to chance level accuracy (AUROC around or below 0.5).

![Figure 5. Detection performance vs. adversarial distortion. Increasing the C&W attack’s confidence parameter $k$ results in more confidently misclassified images with increased transferability, while increasing image distortion. Unlike for our method (red), detection performance (AUROC) on CIFAR10 images drop drastically for the dropout (Feinman et al., 2017) (blue) and MSR (Hendrycks & Gimpel, 2016) (green) methods as $k$ (and adversarial distortion) increase, in both targeted (left) and untargeted (right) UD attacks.](image)

Finally, in Tab. 1 we examine the effect of transformation choice on performance. We tested the ability to detect untargeted C&W attacks using the horizontal flip, Gamma correction and zoom-in transformations, and found they all yield excellent detection performance, often close to perfect (AUROC close to 1). We further experimented with averaging or taking the maximal $D_{KL}$ score over several transformations, and found it yields similar performance to that using individual transformations.

### Table 1. Detecting UD attacks using different transformations. AUROC values reflect detection performance for untargeted UD C&W attacks (with $k = 0$) on the ResNet Inception V2 ImageNet classifier and the CIFAR-10 classifiers from (Carlini & Wagner, 2017a) (“CIFAR-10”) and (Papernot et al., 2016) (“basic”).

| Method          | CIFAR-10 (basic) | CIFAR-10 (ResNet32) | ImageNet (top 5) |
|-----------------|------------------|---------------------|------------------|
| Hor. flip       | 0.936            | 0.976               | 0.966            |
| Gamma$^{0.6}$   | 0.906            | 0.954               | 0.941            |
| Zoom$\times1.05$| 0.932            | 0.974               | 0.964            |

#### 4.1.2. “KNOWN DETECTOR” (KD) PERFORMANCE

We next present experiments with the KD threat model, where an adversary attempts to simultaneously deceive the classifier and bypass the detection mechanism. It should be noted that any detection method can eventually be bypassed, since the attacker could simply replace an image with an alternative natural image from another class, thus achieving desired “wrong” classification. However, such trivial “attacks” are easily visible to a human observer, whereas imperceptible attacks are both more powerful and more interesting from the perspective of understanding vulnerabilities of current visual recognition.

We show that to overcome our detector even with moderate level of success, the attacker needs to modify the original image to a degree that is perceptible to the human eye, in contrast to the much lower distortion imposed by previously proposed detection methods. To this end, we employ the commonly used $L_2$ and $L_{\infty}$ norms (measuring the squared change averaged over pixels, and maximal change over pixels, respectively) to quantify this distortion, and conduct our experiments using a targeted C&W attack (Carlini & Wagner, 2017b) that explicitly minimizes this $L_2$ norm while manipulating images.

The AUROC curves in Fig. 5 show that attacking with higher confidence parameter $k > 0$ is enough to deceive both the dropout (Feinman et al., 2017) and MSR (Hendrycks & Gimpel, 2016) methods, while imposing imperceptible distortion. However, this approach is clearly ineffective against our method, that requires much higher, perceptible, distortion in order to be breached.

To make the attack more credible, we adopted the following successful approach from (Carlini & Wagner, 2017a) as our KD attack: We define a new function $G(x)$ that represents the combination of a given $N$ classes classifier $F$ with logits $\{Z(x)_i\}_{i=1}^N$, and our detectors’ output score, $D_{KL}(x)$. $G$ is a classifier with $N + 1$ classes. It classifies image $x$ according to $F$ (i.e. as belonging to one of the $N$ classes) whenever our detection score is below a pre-defined detection threshold $r$, and classifies $x$ as an “adversarial” (class $N + 1$)
We find the temperature $T$ in Eq. (1) to have a dramatic effect on the detection performance. Setting $T = 1$ (rows 1-3 in Tab. 2) allows the attack to evade detection in almost 100% of images while imposing only slight, imperceptible, increase in distortion. However, lowering the softmax temperature parameter $T$ (Eq. 1) dramatically increased our method’s robustness. Rows 4-6 corresponding to $T \approx 0.15$ show that our method prevents almost half the adversarial attacks, and requires an order-of-magnitude increase in average distortion (row 5) of those images that do bypass it successfully, compared to the UD attack (row 0). This degree of distortion is no longer imperceptible to the naked eye, as exemplified in Fig. 6. We emphasize again that in these KD experiments, the attacker has access to full information about the detector, including the value of $T$.

To understand the effect of the temperature parameter $T$ in Eq. 1, recall that in the KD scenario the adversary attacks the combined classifier-detector model $G$. This means the adversary creates images that simultaneously manage to deceive the classifier, $F(x) \neq y$, and maintain small distance (measured using $D_{KL}$) between the outputs corresponding to the original and transformed images, $F(x)$ and $F(t(x))$, respectively. Setting lower $T$ focuses this distance computation on the few top ranking classes, rather than evenly weighing the entire softmax distribution. This makes the adversary’s task considerably more difficult.

We have also experimented with untargeted KD attacks (an easier task for the attacker, with much more flexibility). Here too we observed the detector forcing higher perturbations in the images to bypass the detector, but not rising to the level easily perceptible to humans ($L_2 = 1.4, L_\infty = 19.5$). However ImageNet has many closely related classes, e.g., similar breeds of dogs. This high inter-class similarity renders untargeted attacks in this domain somewhat less interesting.

### 4.2. Natural error detection

We next evaluate the enhanced natural error detection performance. Our detector is a fully connected network with two hidden layers of width 30, each followed by RELU nonlinearity, and a batch normalization layer. We train it
Table 3. Detecting natural errors. Comparing detection performance (AUROC) of our method with the MSR, dropout and SOTA DBC methods. We detect using either hor. flip based D_KL score or an MLP (based on the hor. flip, Gamma correction, contrast modification, gray-scale conversion and small horizontal blur transformations). Performance is compared using classifiers pre-trained by the DBC work, using either solely cross entropy loss (Regular) or its combination with an adversarial loss term (AT), for their improved performance.

|          | STL-10 | CIFAR-100 |
|----------|--------|-----------|
|          | Regular | AT | Regular | AT |
| MSR      | 0.806  | 0.813 | 0.834  | 0.842 |
| Dropout  | 0.803  | 0.809 | 0.834  | 0.847 |
| DBC      | 0.786  | 0.866 | 0.782  | 0.858 |
| D_KL (Ours) | 0.814  | 0.801 | 0.835  | 0.825 |
| MLP (Ours) | 0.846  | 0.868 | 0.864  | 0.869 |

We augment our detector’s training set by randomly applying horizontal flip and random brightness and contrast adjustments (and for ImageNet also random cropping). This data augmentation pipeline is performed before applying our (fixed) transformations t.

We evaluate our method on the STL-10 and CIFAR-100 datasets, and compare it to MSR (Hendrycks & Gimpel, 2016), dropout (Feinman et al., 2017) and the SOTA Distance Based Confidence (DBC) method by Mandelbaum and Weinshall (2017). DBC detects natural errors by accessing the classifier’s internal activations.

Table 3 present Area Under ROC (AUROC) values obtained using two types of pre-trained classifiers of (Mandelbaum & Weinshall, 2017). These two types differ in the loss function utilized for their training: The Regular classifier used only the cross entropy loss. The AT classifier was fine-tuned using the adversarial loss term of (Goodfellow et al., 2014).

Using our basic D_KL score yields favorable performance on the regular classifiers. However, using our MLP detector achieves the best performance on all classifiers and datasets. Note that while our detector can be used on any given, pre-trained, classifier, it achieves SOTA performance even on classifiers that were modified by the DBC method in its favor (the AT configuration).

ImageNet Finally, we evaluated our natural error detection performance (with and without using an MLP) when applied to the ILSVRC-2012 ImageNet classification task. We used a pre-trained Inception-ResNet-v2 model (Szegedy et al., 2016) that achieves 81% and 95.5% top-1 and top-5 accuracies, respectively. As before, we used part of ImageNet’s validation set to train our detector (20% in this experiment), and evaluated its performance on the remaining part. Table 4 compares AUROC values corresponding to ours and the MSR (Hendrycks & Gimpel, 2016) methods. Due to the scale of ImageNet, we did not compare to methods that require either extensive re-training (DBC) or extensive computation (dropout).

Table 4. Detecting natural errors on ImageNet. Comparing detection performance (AUROC) of our method using either D_KL score or an MLP (both based on the same transformations as in Tab. 3), with the MSR method. Tested on a pre-trained Inception-ResNet-V2 classifier.

|          | Top-1 | Top-5 |
|----------|-------|-------|
| MSR      | 0.842 | 0.806 |
| D_KL (Ours) | 0.852 | 0.823 |
| MLP (Ours) | **0.875** | **0.884** |

5. Conclusions

We devise a simple & robust classification error detector based on our observation that incorrect predictions correspond to less stable classifier outputs under a set of image transformations. We demonstrate the effectiveness of this approach for rejecting adversarial examples, under a variety of attack scenarios, including the most challenging Known Detector (KD) attack by the Carlini & Wagner method. We further propose to enhance detection of natural errors by training an Inception based MLP. Beyond the immediate applications to increase robustness and reduce classifiers’ vulnerability, the success of our detection methods suggests further study of invariance of convolutional networks under image transformations, and the potential role this invariance may play in improving recognition.

We avoid training our MLP on images that were used for the classifiers’ training, to avoid train/test disparity since the classifier had a chance to optimize its output on the training images. Instead we train the detector on a subset of the validation set. The subset assignment for each data-set is consistent across all our experiments, and will be made public, along with our code.

Another comparison on a third loss term proposed in (Mandelbaum & Weinshall, 2017) yielded similar results, omitted here for lack of space. When using their classifier, we follow (Mandelbaum & Weinshall, 2017) and pre-process the original and transformed images by global contrast minimization and ZCA whitening.
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