Familiarity-Based Open-Set Recognition Under Adversarial Attacks

Enevoldsen, Philip; Gundersen, Christian; Lang, Nico; Belongie, Serge; Igel, Christian

Publication date:
2023

Document version
Publisher's PDF, also known as Version of record

Document license:
CC BY

Citation for published version (APA):
Familiarity-Based Open-Set Recognition Under Adversarial Attacks

Philip Enevoldsen* Christian Gundersen* Nico Lang Serge Belongie Christian Igel
Department of Computer Science, University of Copenhagen

Abstract

Open-set recognition (OSR), the identification of novel categories, can be a critical component when deploying classification models in real-world applications. Recent work has shown that familiarity-based scoring rules such as the Maximum Softmax Probability (MSP) or the Maximum Logit Score (MLS) are strong baselines when the closed-set accuracy is high. However, one of the potential weaknesses of familiarity-based OSR are adversarial attacks. Here, we present gradient-based adversarial attacks on familiarity scores for both types of attacks, False Familiarity and False Novelty attacks, and evaluate their effectiveness in informed and uninformed settings on TinyImageNet.

1. Introduction

In many real-world applications of machine learning models, it is crucial to understand the models’ limitations and the trustworthiness of their predictions in novel situations. Thus, we investigate open-set recognition (OSR) [18], which can be seen as a special case of out-of-distribution (OOD) detection [23], where the task is to identify novel categories at test time, which were not included in the training dataset. Recently, Vaze et al. [22] have demonstrated that the progress in OSR performance over the past years is not necessarily due to advancement in OSR approaches, but is correlated with improved performance on the closed-set categories, i.e. the classification of categories included in the training dataset. With this observation, simple baseline scoring rules such as the Maximum Softmax Probability (MSP) [8] and the Maximum Logit Score (MLS) [22, 7] are competitive and perform on par with—or even outperform—more dedicated approaches such as ARPL and ARPL+CS [2], OSRCI [15], and OpenHybrid [24]. At the same time, Dietterich & Guyer [3] have proposed the Familiarity Hypothesis, stating that such familiarity-based scoring rules identify novel categories by measuring the absence of familiar features instead of actively recognizing the presence of novel features. They investigated occlusions as one of the weaknesses of familiarity-based OSR, which can cause false novelty detections. Adversarial attacks pose another potential weakness to familiarity-based OSR, which we study in this work. Dietterich & Guyer [3] mention the risks of adversarial vulnerability in their outlook discussion:

“By applying existing attack algorithms (e.g., the FGSM [6]), we predict that it will be very easy to raise the logit score of at least one class and thereby hide a novel class image from novelty detection. It may also be possible to depress the logit scores of enough classes to create false anomaly alarms.”

In other words, this prediction states that it might be trivial

\*Equal contribution.
to compute adversarial perturbations that amplify familiar features to 
am cause a false familiarity, but it might be harder to 
hide (all) familiar features to yield a false novelty (See 
Fig. 1). While it has been shown that the OSR approach 
OpenMax [1] is vulnerable to adversarial attacks [19, 20], 
we study the vulnerability of familiarity-based OSR ap-
proaches to gradient-based adversarial white-box attacks 
(i.e., the model parameters are given) by formulating 
three main questions:

1. **False Familiarity vs. False Novelty**: What type of 
attack is more effective?

2. **FGSM vs. iterative attacks**: Is it worth exploring 
more flexible iterative attacks to improve upon the fast 
gradient sign method (FGSM)?

3. **Uninformed vs. informed attacks**: How can ad-
versarial attacks profit when the type of input is given 
(i.e., closed-set or open-set sample)?

### 2. Methodology

#### 2.1. Familiarity-based open-set recognition (OSR)

We consider an input space $X$ and a set $F$ of familiar 
categories, i.e. the closed-set. In closed-set recognition 
(CSR), the objective is to model the probability $p(y \mid x, y \in F)$, 
where $y$ is a label that is associated with the input $x \in X$. 
The model is trained on a training dataset $D_{\text{train}} = \{(X_i, y_i)\}_{i=1}^N \subset X \times F$ 
evaluate on a non-overlapping 
closed-set test set, $D_{\text{test-csr}} = \{(X_i, y_i)\}_{i=1}^M \subset X \times F$ that 
contains the categories given at train time. We consider a 
deep neural network $f_\theta : X \rightarrow \mathbb{R}^{|F|}$ parameterized by $\theta$ 
for modelling $p(y \mid x, y \in F)$. Here, $f_\theta$ maps an input to a 
vector of logits that are normalized using the softmax func-
tion $\sigma : \mathbb{R}^{|F|} \rightarrow (0, 1)^{|F|}$ to obtain pseudo-probabilities for 
the familiar categories.

In the open-set recognition (OSR) setting a set $N$ of 
novel categories is additionally considered and a test set 
containing inputs from both novel and familiar classes 
is used to evaluate the OSR performance: $D_{\text{test-osr}} = \{(X_i, y_i)\}_{i=1}^N \subset X \times (F \cup N)$. A balanced test set containing 
an equal number of familiar and novel samples is 
typically used to evaluate the OSR performance. To de-
decide whether $y \in F$, a familiarity score, $S(y \in F \mid x)$, is 
modelled to rank the test samples in $D_{\text{test-osr}}$. Familiarity-
based scoring rules include the Maximum Softmax Prob-
ability (MSP) score [8]:

$$S_{\text{MSP}}(y \in F \mid x) := \max_y \sigma(f_\theta(x))_y$$

and the Maximum Logit Score (MLS) [22, 3]:

$$S_{\text{MLS}}(y \in F \mid x) := \max_y f_\theta(x)_y,$$

which has outperformed the MSP score in prior work [22]. 
For both scoring rules, high scores indicate familiar and low 
scores indicate novel categories.

#### 2.2. Fast gradient sign method (FGSM)

A simple and effective method for generating adversarial 
inputs is the Fast Gradient Sign Method (FGSM) which was 
first described by [6]. The FGSM generates an adversarial 
input, $x_{\text{adv}}$, using the following equation:

$$x_{\text{adv}} = x + \varepsilon \text{ sign} [\nabla_x L(\theta, x, y)]$$

Here $x$ represents the unmodified input and the second term 
is known as the adversarial perturbation, where $\varepsilon$ controls 
the magnitude of the perturbation. Initially, $L$ is set to the 
training objective [6], but can be any objective function that 
an adversary aims to optimize. The adversarial perturbation 
is constrained such that $\|x_{\text{adv}} - x\|_\infty \leq \varepsilon$.

#### 2.3. Iterative attacks

Iterative approaches can generate more diverse perturba-
tions compared to the FGSM by optimizing the objective 
function in a more flexible manner but at higher computa-
tional costs. The Basic Iterative Method (BIM) [12] applies 
the FGSM update iteratively and is described by:

$$x_{\text{adv}}^{(0)} = x$$

$$x_{\text{adv}}^{(n+1)} = \text{Clip}_{\varepsilon}(x_{\text{adv}}^{(n)} + \alpha \text{ sign} [\nabla_x L(\theta, x_{\text{adv}}^{(n)}, y)])$$

In this method, the step size $\alpha$ and the number of iterations 
can be adjusted to get the desired trade-off between run-
time and performance. Alternative approaches are inspired 
by gradient-based optimizers using momentum to improve 
performance [4]. We investigate an iterative approach using 
RPROP [16, 5] that relaxes the fixed step size $\alpha$ of BIM 
with an adaptive step size:

$$x_{\text{adv}}^{(n+1)} = \text{Clip}_{\varepsilon}(x_{\text{adv}}^{(n)} + \text{Step}(L, \theta, x_{\text{adv}}^{(n)}, y))$$

where Step($L, \theta, x_{\text{adv}}^{(n)}, y$) denotes the update step computed 
by some iterative optimization method. RPROP adjusts the 
step size separately for every optimizable parameter while 
iterating—in the case of adversarial attacks on images for 
every pixel per channel. Adversarial perturbations created 
with RPROP can be sparse and may therefore be less notice-
able. For a fair comparison with FGSM, the perturbations 
are clipped to $\varepsilon$.

#### 2.4. Adversarial attacks on familiarity-based OSR

**False Familiarity (False Negative, FN)**: False Familiar-
ity attacks aim to *increase* the logit (or softmax probability) 
of an arbitrary familiar category, which is similar to targeted 
attacks in closed-set recognition [11]. We investigate three
Figure 2: Uninformed FGSM attacks. Fast gradient sign method (FGSM) attacks on TinyImageNet. Left: False Familiarity (false negative, FN) attacks. Right: False Novelty (false positive, FP) attacks. (a,b) The OSR ranking measured by AUROC. (c,d) Median Maximum Logit Score (MLS) w.r.t. original scores. (e,f) Qualitative examples of adversarial perturbation.

Objective functions to achieve this attack:

\[ L_{\text{max}}(\theta, x, y) = \max_y f_\theta(x)_{y'} \]  
\[ L_{\text{2-norm}}(\theta, x, y) = ||f_\theta(x)||_2 \]  
\[ L_{\text{log-MSP}}(\theta, x, y) = \log \max_{y'} \sigma(f_\theta(x))_{y'} \]

The log-MSP loss has been proposed in the ODIN approach [14] (which was refined in the generalized ODIN [9]) to preprocess images with adversarial perturbations to improve OOD detection using the MSP score.

False Novelty (False Positive, FP). In this likely more challenging setting, we may have to decrease the logits of multiple categories either with a single FGSM step or multiple iterative steps. Objective functions rewarding only the decrease of the largest logit might fail, thus, besides the \( L_{\text{max}} \), we investigate the \( L_{\text{2-norm}} \) and the sum-exp loss:

\[ L_{\text{sum-exp}}(\theta, x, y) = \sum_{y' \in |F|} e^{f_\theta(x)_{y'}} \]

The 2-norm encourages reducing non-maximum logits while still prioritizing the max logit. However, one limitation of the 2-norm is that it is non-negative. Since logits are unnormalized and can be negative, it would be preferable if the objective function also rewarded making the logits negative. This led us to propose the sum-exp loss, which continues to decrease if a logit becomes negative.

Importantly, while False Familiarity attacks maximize these objectives, False Novelty attacks minimize them.

Uninformed vs. informed attacks. We call an attack informed if the adversary has access to the binary set-labels of the input, i.e. closed-set vs. open-set, and uninformed if that information is not available [10]. In the uninformed setting, either a FP or FN attack is applied on all images, disregarding whether an image is novel or familiar. For informed adversaries, FN attacks are performed on novel images and FP attacks on familiar images only.

\footnote{While this is not further investigated in this work, our OSR experiments did not confirm an improvement of the MSP score as also mentioned in other independent work [5].}
Figure 3: Informed attacks. False Positive (FP) attacks are performed on familiar samples (2-norm loss) and False Negative (FN) attacks on novel samples (max loss). (a) Fast gradient sign method (FGSM) using $\epsilon = 0.07$ for FN and $\epsilon = 0.06$ for FP. (b) Our iterative method with $\epsilon = 0.07$ for FN and $\epsilon = 0.04$ for FP attacks.

3. Experimental results

We experiment with the TinyImageNet dataset [13], described as one of the most challenging benchmarks used in the OSR literature [22]. Here we use the open-set split presented in Vaze et al. [22] and follow their experimental setup. TinyImageNet consists of a subset of 200 ImageNet categories [17], whereas 20 classes are used as the closed-set training dataset and 180 classes as the open-set. The CNN architecture used is a VGG32, a lightweight version of the VGG architecture [21]. This results in a reproduced closed-set accuracy of 84.2% averaged over five class splits.

We report the OSR performance of the MLS for the first of the five splits with the area under the Receiver-Operator curve (AUROC). The AUROC is a threshold-less metric that evaluates the ranking from open-set to closed-set samples. As a higher AUROC means better OSR performance, adversarial attacks aim to lower the AUROC.

What type of attack is more effective? It depends. In the uninformed FGSM experiments, False Novelty (False Positive, FP) attacks are more effective in destroying the ranking, i.e. decreasing the AUROC, than False Familiarity (False Negative, FN) attacks at the same magnitude $\epsilon$ of adversarial perturbation (Fig. 2a, 2b). However, we observe the opposite in the informed setting (Fig. 3), where the AUROC of FN attacks is lower than FP attacks. To understand this behaviour, we look at the distribution of scores before and after the attacks.

It is too easy to raise the logit score. Or in other words, to amplify familiar features. While FN attacks aim to amplify familiar features of the open-set to cause a missed novelty, in contrast, FP attacks aim to hide familiar features to reduce the familiarity of closed-set categories. We recall that uninformed attacks are performed on both novel and familiar images. Even though FN attacks can increase the median MLS above the 99th percentile of the original test data scores (Fig. 2c), the AUROC is rather preserved (Fig. 2a). Hence, the FN attacks not only increase the familiarity (i.e.; MLS) of the novel but also of the familiar samples, which preserves the ranking. In contrast, FP attacks cannot decrease the median MLS below the 1st percentile of the original test scores, but the ranking (AUROC) is effectively destroyed. This suggests that FP attacks tend to decrease the scores of the closed-set more than the scores of the open-set. Our experiments confirm the prediction of Dietterich & Guyer [3] that it is very easy to raise the logit score, which only leads to effective FN attacks in the informed setting. However, our results reveal that for uninformed attacks the ability to easily raise the logit score is not the key to attack the ranking of familiarity-based OSR approaches.

Which objective function performs best? While some objective functions are able to perform both types of attacks by swapping the sign, no objective is clearly best for both FN and FP attacks (Fig. 2a, 2b). FGSM FN attacks achieve lowest AUROC using the Log-MSP loss and second lowest with the Max loss. For FP attacks the Max loss achieves the lowest AUROC with $\epsilon < 0.1$. Whereas at $\epsilon \approx 0.3$ all objective functions achieve an AUROC of $\approx 0.5$, for $\epsilon > 0.3$ the 2-Norm achieves even lower AUROC.

FGSM vs. iterative attacks. Informed iterative attacks are able to decrease the AUROC by an order of magnitude compared to informed FGSM attacks using the same or even smaller $\epsilon$ (Fig. 3). The AUROC for FP attacks is decreased from 0.34 (FGSM) to 0.06 (iterative) and for FN attack from 0.12 (FGSM) to 0.01 (iterative).

Informed attacks reverse the ranking almost perfectly. Informed FGSM attacks can improve substantially over uninformed attacks. Informed FGSM and iterative attacks are able to reverse the ranking of novel and familiar images almost perfectly when using both FP attacks on familiar and FN attacks on novel samples together (Fig. 3).

4. Conclusion

We have studied the vulnerability of familiarity-based OSR approaches to adversarial attacks. Our MLS experiments confirm Dietterich & Guyer’s [3] prediction that the logit score can be easily increased with an adversarial perturbation. However, this ability leads only to effective False Familiarity (FN) attacks in the informed setting. In an uninformed setting, FN attacks are less effective than FP attacks that, in contrary, are able to successfully destroy the ranking by hiding familiar features of closed-set categories. The uninformed setting may be informative for the development of new scoring rules. It remains to be tested if the observed adversarial robustness holds for alternative familiarity scores.
such as the MSP. We hope that our findings can contribute to the design of better scoring rules in the future and to make familiarity scores robust to adversarial attacks.

Acknowledgement

P.E. and C.G. acknowledge support by the Danish Data Science Academy (DDSA) travel grant. N.L., S.B., and C.I. acknowledge support by the Pioneer Centre for AI, DNRF grant number P1.

References


[22] Sagar Vaze, Kai Han, Andrea Vedaldi, and Andrew Zisserman. Open-set recognition: A good closed-set classifier is all you need. In The Tenth International Conference on Learning Representations (ICLR), 2022.
