ARAE: Adversarially Robust Training of Autoencoders Improves Novelty Detection

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Abstract. Autoencoders (AE) have recently been widely employed to approach the novelty detection problem. Trained only on the normal data, the AE is expected to reconstruct the normal data effectively while fail to regenerate the anomalous data, which could be utilized for novelty detection. However, in this paper, it is demonstrated that this does not always hold. AE often generalizes so perfectly that it can also reconstruct the anomalous data well. To address this problem, we propose a novel AE that can learn more semantically meaningful features. Specifically, we exploit the fact that adversarial robustness promotes learning of meaningful features. Therefore, we force the AE to learn such features by penalizing networks with a bottleneck layer that is unstable against adversarial perturbations. We show that despite using a much simpler architecture in comparison to the prior methods, the proposed AE outperforms or is competitive to state-of-the-art on three benchmark datasets.

Keywords: Novelty detection, Autoencoder, Adversarial Robust Training, Adversarial attacks

1 Introduction

In many real-world problems, it is easy to gather normal data from the operating behavior of a system. However, collecting data from the same system in situations where it malfunctions or is being used clumsily may be difficult or even impossible. For instance, in a surveillance camera that captures daily activity in an environment, almost all frames are related to the normal behavior. This means that data associated with the anomalous behavior is difficult to obtain from such cameras. Anomaly/novelty detection refers to the set of solutions for such settings.

The key point in the definition of anomaly detection is the outlier notion. In the literature, An outlier is defined as a data point that deviates from the bulk of the remaining data [6,14]. Assuming that the normal data is generated by a distribution, the goal is to detect whether a new unseen observation is drawn from this distribution or not. In the context of anomaly detection, some
outlier detection, abnormal detection, and novelty detection are some of the terms that are widely used in this context. While these terms seem to convey identical concepts, they are slightly different. Outlier or anomaly detection refers to the tasks where the training data includes both outliers and inliers. The goal of the estimator is then to learn a representation of compact regions in the feature space, where most of the normal data points are laid in. This representation is then used to identify the deviant observations as outliers. However, in novelty detection problems, only the normal data is used for the model training [5, 6]. In this work, we assume the novelty detection setting and propose a novel method that achieves results that are competitive or superior to state-of-the-art despite its simplicity. In prior work, AE and Generative Adversarial Network (GAN) were extensively applied for novelty detection [2, 24, 27, 29].

In GAN-based approaches, one tries to train a model that could adversarially generate realistic images from the normal class. This means that if the model fails to generate a given input image, the input would probably be an anomalous one. However, GAN-based approaches face some challenges during the training. These include mode collapse that happens when the generator maps several inputs to a single image in the output space. In GAN, complete mode collapse is rare, while a partial collapse occurs more frequently [11, 17]. Furthermore, high sensitivity of the training to the choices of hyperparameters, non-convergence problem, parameter oscillation, and non-reproducible results due to the unstable training are counted as the other challenges in training of the GAN [22, 28].

On the other hand, AE is more convenient to train and gives results that are easier to reproduce. Therefore, we investigate AE-based approaches in this paper. An AE, which has learned features that are mostly unique to the normal class, could reconstruct the normal data perfectly, while when given an anomalous data, it either reconstructs a corrupted or a normal output; In the former case, the anomalous input is likely to have disjoint features compared to the normal class, while in the latter, the input may resemble a normal data in some aspects. Note that in both cases, unlike for the normal data, the reconstruction Mean Squared Error (MSE) is high for the anomalous data. This means that for such an AE, we could threshold the reconstruction loss to distinguish the normal vs. anomalous data. One could alternatively leverage a discriminator that is applied to the reconstructed image to distinguish between the anomalous and normal data [18, 27]. In any case, as mentioned, an important premise for the AE to work is that it learns mostly unique features to the normal class. We call such features “semantically meaningful” or “robust”, contrasted with generic low level features that are subject to change in presence of noise, in the rest of the paper.

A common problem in using AE for novelty detection is its generalization ability to reconstruct some anomaly inputs, when they share common features with the normal class [10, 45]. Although this generalization property is useful in other contexts, such as restoration [21], it is considered as a drawback in novelty detection. In other papers [13, 54], the main underlying assumption behind the AE-based approaches is that the reconstruction error is high when the model
is given an anomalous data, which as mentioned does not seem to be holding perfectly.

There are two reasons why the main underlying assumption in these methods does not hold necessarily. First, the model behavior when facing the anomalous data is not observed and is not therefore predictable. Second, the learned latent space may capture mostly the features that are in common between the normal and anomalous data. When given the anomalous data, this would likely yield a perfectly reconstructed anomalous data. To address these issues, we aimed for a solution that learns an adversarially robust latent space, where the focus is on learning unique or semantically meaningful features of the normal inputs and their nuances. This could prevent the decoder from reconstructing the anomalies.

It is shown in [20] that small imperceptible changes in the input can easily fool a deep neural network classifier. AE’s are subject to such attacks as well. This stems from the fact that a deep classifier or an AE would likely learn low level or brittle non-robust features [15]. Low level features could be exploited to reconstruct any given image perfectly. Hence, the presence of such features seems to violate the main underlying assumption of the earlier work for novelty detection that is based on AE. Therefore, we propose to train an adversarially robust AE to overcome this issue. In Fig. 1, reconstructions from Denoising Autoencoder (DAE) and the proposed method are shown. Here, the normal data is considered to be the number 8 in the MNIST dataset and the models are trained only on the normal category. As opposed to the proposed Adversarially Robust trained Autoencoder (ARAE), DAE generalizes and reconstructs the number 1 perfectly. This is not desired in the novelty detection problem. This means that the latent space of DAE has learned features that are not necessarily meaningful.

![Fig. 1: Unlike DAE, ARAE that is trained on the normal class, which is the digit 8, reconstructs a normal instance when it is given an anomalous digit, from the class 1. The first row shows the input images. The second and third rows show DAE and ARAE reconstructions of the corresponding inputs, respectively. ARAE is trained based on bounded $\ell_\infty$, $\ell_2$, rotation, and translation perturbations.](image)

To train a robust AE for the novelty detection task, a new objective function based on adversarial attacks is proposed. The novel AE which is based on a simple architecture, is evaluated on the MNIST, Fashion-MNIST, and COIL-100
datasets. We will next review existing approaches in more details, and then describe our proposed idea along with its evaluation. We demonstrate that despite the simplicity of the underlying model, the proposed model outperforms or stays competitive with state-of-the-art in novelty detection.

2 Related work

As explained earlier in the introduction, methods that are used in the literature are classified into two main categories: (1) modeling the normal behavior in the latent space; and (2) thresholding the AE reconstruction error. Of course, a hybrid of these two approaches was also considered in the field.

OCGAN [44], takes the second approach, i.e. it is based on the MSE distance between the AE output and its input. An underlying assumption in this work is that the training data may contain abnormal samples. Therefore, the method tries to identify these samples throughout the training process. It finally uses only the reconstruction error in the test time. As an extension to the AE-based methods, in [24], a model is introduced in which the AE is trained by using 4 GANs, a classifier, and the “negative sample mining” technique. Here, both the encoder and decoder of the AE are considered as generators in the GAN. At the inference time, the method only uses MSE between the model output and input to make a prediction. The authors attempted to force the encoder output distribution to be approximately uniform. They also forced the decoder output distribution to resemble the normal input distribution in the whole latent domain. This is expected to result in a higher MSE distance between the decoder output and input for the abnormal data. This method achieved state-of-the-art results at the time of presentation.

[1] and [27] are the other examples in the AE-based approaches, except that in [1], additionally, the probability distribution over the latent space was obtained for the normal input data. Then, in the test time, the probability of a sample being normal, which is called the “surprise score”, is added to the reconstruction error before the thresholding happens. [15] used a similar approach to [1], except that the probability distribution of the normal data in the latent space is not obtained by an auto-regressive model, but is computed by a Gaussian Mixture Model. One of the benefits of this method is the ability to train the deep network in an end-to-end manner to implement the EM algorithm. During the test, a vector, which is summarizing the reconstruction error in AE using various distance metrics is computed and concatenated to the AE latent feature vector. Then, the resulting vector is fed into an estimator network that detects the normal data based on a proposed energy criteria. In [27], there is a possibility of using the discriminator output, which is a real number between zero and one, as an alternative to the MSE distance in order to find the anomaly score. This is done by considering the AE as the generator in the GAN framework.

Following the first general approach of modeling the normal behavior in the latent space. [12] uses Variational Autoencoder (VAE) for training and attempts to find disentangled latent features in order to model the inter-class and intra-class variations of normal samples in disjoint dimensions. Then, it only uses the
encoder output as input to a classifier to detect the abnormal data. In [25], a GAN is initially used to obtain the latent space, then the probability distribution of the normal class over the latent space is considered to be as the multiplication of two marginal distributions, which are learned empirically. [26] (DSVDD) tries to model the normal latent space with the presumption that all normal data can be compressed into a hyper-sphere. This framework can be considered as a combination of Deep Learning and classical models such as [7] (One-class SVM), that has the advantage of extracting more relevant features from the training data than the above-mentioned [7] because the whole network training process is done in an end-to-end procedure. In [29], a GAN framework is used to model the latent space. It is assumed that if the test data is normal, then a sample could be found in a latent space such that the corresponding image that is made by the generator is classified as real by the GAN discriminator. It should be noted that the method needs to solve an optimization problem at the test time in order to find the corresponding latent features of a given input. This, however, prevents the inference procedure from being real-time.

3 Method

As we discussed earlier, the main problem of AE is its strong generalization ability. We observe that DAE does not necessarily learn distinctive features of the normal class. To remedy this problem, our approach is to force the AE latent space implicitly to model only unique features of the normal class. To make this happen, the framework for adversarial robustness, which is proposed in [15,20], is adopted. We propose to successively craft adversarial examples and then utilize them to train the AE. Adversarial examples are considered as those irrelevant small changes in the input that destabilize the latent encoding. We will next describe the details of the proposed adversarial training in the following sections.

3.1 Adversarial Examples Crafting

In a semantically meaningful latent space, two highly perceptually similar samples should share similar feature encodings. Therefore, searching for a sample $X^*$ that is perceptually similar to a sample $X$, but has a distant latent encoding from that of $X$, leads us to an adversarial sample. As opposed to the normal sample $X$, the adversarial sample $X^*$ is very likely to have a high reconstruction loss, thus it would be detected as abnormal by the AE, despite being perceptually similar to a normal sample. Therefore, based on this intuition, the following method is used to craft the adversarial samples.

At the training epoch $i$, we craft a set of adversarial samples $S^i_{(adv)}$ based on the initial training dataset $S$. For this purpose, we slightly perturb each sample $X \in S$ to craft an adversarial sample $X^*$ that has two properties: (1) $X^*$ is perceptually similar to $X$, through controlling the $\ell_\infty$ distance of $X$ and $X^*$; (2) $X^*$ latent encoding is as far as possible from that of $X$. This is equivalent to
solving the following optimization problem:

$$\max_{\delta_X} L_{\text{latent}} \text{ s.t. } \|\delta_X\|_\infty \leq \epsilon, \text{ where } L_{\text{latent}} = \|\text{Enc}(X + \delta_X) - \text{Enc}(X)\|_2^2 . \quad (1)$$

In this formulation, \(\|\cdot\|_p\) is the \(\ell_p\)-norm, \(\epsilon\) is the attack magnitude, and \(X^* = X + \delta_X\) is the adversarial sample. We solve this optimization problem for each sample \(X \in S\) using the Projected Gradient Descent (PGD) \cite{20} method, to obtain \(S^i_{\text{(adv)}}\).

### 3.2 Autoencoder Adversarial Training

To train the AE using the crafted dataset \(S^i_{\text{(adv)}}\) in the previous section, we propose the following loss function:

$$L_{\text{AE}} = L_{\text{rec.}} + \gamma L_{\text{latent}} \quad (2)$$

where \(\gamma\) is a balancing hyperparameter, \(L_{\text{latent}}\) refers to the loss function that is introduced in Eq. (1) and \(L_{\text{rec.}}\) corresponds to the following loss function:

$$L_{\text{rec.}} = \|X - \text{Dec}(\text{Enc}(X^*))\|_2^2 . \quad (3)$$

At each step, the AE is trained one epoch on the adversarial crafted samples using this loss function. The training procedure is demonstrated in Fig. 2. In the training procedure, the \(L_{\text{rec.}}\) term forces the AE to reconstruct the adversarial samples properly, while the \(L_{\text{latent}}\) term forces the adversarial samples to have closer representations to that of the corresponding normal samples in the latent space. We observe that the encoder decreases \(L_{\text{latent}}\) to a limited extent by merely encoding the whole input space into a compact latent space. Too compact latent...
space results in a high $L_{\text{rec.}}$, which is not achievable when the network is trained using $L_{AE}$. To summarize, the whole training procedure is trying to solve the following saddle point problem \cite{35}:

$$\delta^*_X := \arg \max_{\\|\delta_X\|_\infty \leq \varepsilon} L_{\text{latent}}(X, \delta_X, W)$$

$$\min_W \mathbb{E}_X [\gamma L_{\text{latent}}(X, \delta^*_X, W) + L_{\text{rec.}}(X, \delta^*_X, W)],$$

where $W$ is denoted as the AE weights. Note that it was shown that the adversarial training could not be solved in a single shot by the Stochastic Gradient Descent (SGD), and one instead should try other optimization algorithms such as the PGD. This relies on Danskin theorem to solve the inner optimization followed by the outer optimization \cite{20}.

4 Experiments

In this section, we evaluate our method, which is denoted by ARAE, and compare it with state-of-the-art on common benchmark datasets that are used for the unsupervised novelty detection task. We show that even though our method is based on a simple and efficient architecture, it performs competitively with state-of-the-art approaches. The results are based on several evaluation strategies that are used in the literature. All results that are reported in this paper are reproducible by our publicly available implementation in the Keras framework \cite{8}.

4.1 Experimental Setup

Datasets. We evaluate our method on MNIST \cite{19}, Fashion-MNIST \cite{38}, and COIL-100 \cite{23} datasets. Next, we briefly introduce each of these datasets.

- MNIST: This dataset contains 70,000 $28 \times 28$ grayscale handwritten digits from 0 to 9.
- Fashion-MNIST: A dataset similar to MNIST with 70,000 $28 \times 28$ grayscale images of 10 fashion product categories.
- COIL-100: A dataset of 7200 color images of 100 different object classes. Each class contains 72 images of one object captured in different poses. We downscale the images of this dataset to the size $32 \times 32$.

Protocols. To carry out the training-testing procedure, we need to define the data partitions. For MNIST and Fashion-MNIST, one class is considered as the normal class and samples from the other classes are assumed to be anomalous. For COIL-100, we randomly take $n$ classes as the normal classes, where $n \in \{1, 4, 7\}$, and use the samples from the remaining classes as the anomalous samples. For the mentioned dataset, this process is repeated 30 times and

\footnote{https://github.com/rohban-lab/Salehi_submitted_2020}
the results are averaged. To form the training and testing data, there are two protocols that are commonly used in the framework of unsupervised novelty detection \cite{24,25,27}, which are as follows:

- **Protocol 1**: The original training-testing splits of the dataset are merged, shuffled, and 80% of the normal class samples are used to train the model. The remaining 20% forms some specified portion of the testing data. The other portion is formed by randomly sampling from the anomalous classes.

- **Protocol 2**: The original training-testing splits of the dataset are used to train and test the model. The training is carried out using the normal samples and the entire testing data is used for evaluation.

We compare our method to other approaches using Area Under the Curve (AUC) of the Receiver Operating Characteristics (ROC) curve, the $F_1$ score, and the False Positive Rate (FPR) at 99.5% True Positive Rate (TPR). Here, we let the positive class be the anomalous one unless otherwise specified.

**Architecture and Hyperparameters.** Our AE uses a 3-layer fully connected network with layer sizes of $(512, 256, 128)$, following the input-layer to encode the input. A decoder, whose architecture is mirroring that of the encoder, is used to reconstruct the output. Each layer of the network is followed by a sigmoid activation. For datasets with complex and detailed images like COIL-100 and Fashion-MNIST, the hyperparameter $\epsilon$, which is the maximum perturbation $\ell_\infty$ norm as defined in Eq. 4, is set to 0.05, while for MNIST it is set to 0.2. The hyperparameter $\gamma$, defined in Eq. 4, is always set to 0.1.

### 4.2 Results

We present our AUC results for MNIST and Fashion-MNIST datasets in Tables 1 and 2. The tables contain AUC values for each class as the normal class, which were achieved using protocol 2. We compare our results against current state-of-the-art and baseline methods. We train a DAE, as a baseline method, with a random uniform noise between 0 and 0.1 using the same network as the one that is used in our approach. AUC values of some methods were obtained from \cite{24,36}.

Furthermore, in Table 3 we compare our results for the COIL-100 dataset to the results reported in \cite{25}. This table contains AUC and $F_1$ values for $n \in \{1, 4, 7\}$, where $n$ is the number of normal classes. We use protocol 1 for this dataset. For each $n \in \{1, 4, 7\}$, the percentage of the anomalous samples in the training data is defined in the table. The $F_1$ score is reported for the threshold value that is maximizing it.

As shown in Tables 1, 2, and 3, we achieve state-of-the-art results in all of these datasets while using a simpler architecture compared to other state-of-the-art methods, such as OCGAN, LSA, GPND, and R-graph.

We also evaluate our method using the $F_1$ score on the MNIST dataset in Table 4. In order to do this, we use the $F_1$ scores reported in \cite{25}. In this experiment, the normal class is the positive one. We use protocol 1 and vary the
anomaly percentage between 10% and 50%. We use 20% of the training samples and sample from the anomalous classes to form a validation set with the same anomaly percentage as the testing data. This validation set is used to find the threshold that maximizes the $F_1$ score.

As shown in Fig. 3 (left), we achieve slightly lower $F_1$ scores compared to that of GPND. However, this figure shows the low impact of the percentage of anomalous data on our method performance.

FPR values at 99.5% TPR of MNIST dataset for ARAE and DAE are reported in Table 5 and compared in Fig. 3 (right). As reported in the table, ARAE decreases the FPR value by more than half in classes 0, 3, and 6.

Table 1: AUC values for the MNIST dataset. The values were obtained for each class using protocol 2.

| Method  | 0   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | Mean |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| VAE \[16\] | 98.5 | 99.7 | 94.3 | 91.6 | 94.5 | 92.9 | 97.7 | 97.5 | 86.4 | 96.7 | 95.0 |
| OCSVM \[7\] | 99.5 | 99.9 | 92.6 | 93.6 | 96.7 | 95.5 | 98.7 | 96.6 | 90.3 | 96.2 | 96.0 |
| AnoGAN \[29\] | 96.6 | 99.2 | 85.0 | 88.7 | 89.4 | 88.3 | 94.7 | 93.5 | 84.9 | 92.4 | 91.3 |
| DSVDD \[26\] | 98.0 | 99.7 | 91.7 | 91.9 | 94.9 | 88.5 | 98.3 | 94.6 | 93.9 | 96.5 | 94.8 |
| MTQM \[56\] | 99.5 | 99.8 | 95.3 | 96.3 | 96.6 | 96.2 | 99.2 | 96.9 | 95.5 | 97.7 | 97.3 |
| OCGAN \[24\] | 99.8 | 99.9 | 94.2 | 96.3 | 97.5 | 98.0 | 99.1 | 98.1 | 93.9 | 98.1 | 97.5 |
| LSA \[1\] | 99.3 | 99.9 | 95.9 | 96.6 | 96.4 | 96.4 | 99.4 | 98.0 | 95.3 | 98.1 | 97.5 |
| DAE | 99.6 | 99.9 | 93.9 | 93.5 | 96.4 | 94.3 | 99.0 | 95.8 | 89.1 | 97.5 | 95.9 |
| ARAE | 99.8 | 99.9 | 96.0 | 97.2 | 97.0 | 97.4 | 99.5 | 96.9 | 92.4 | 98.5 | 97.5 |

Table 2: AUC values for the Fashion-MNIST dataset. The values were obtained for each class using protocol 2.

| Method  | 0   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | Mean |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| VAE \[16\] | 87.4 | 97.7 | 81.6 | 91.2 | 87.2 | 91.6 | 73.8 | 97.6 | 79.5 | 96.5 | 88.4 |
| OCSVM \[7\] | 91.9 | 99.0 | 89.4 | 94.2 | 90.7 | 91.8 | 83.4 | 98.8 | 90.3 | 98.2 | 92.8 |
| DAGMM \[45\] | 30.3 | 31.1 | 47.5 | 48.1 | 49.9 | 41.3 | 42.0 | 37.4 | 51.8 | 37.8 | 41.7 |
| DSEBM \[12\] | 89.1 | 56.0 | 86.1 | 90.3 | 88.4 | 85.9 | 78.2 | 98.1 | 86.5 | 96.7 | 85.5 |
| MTQM \[56\] | 92.2 | 95.8 | 89.9 | 93.0 | 92.2 | 89.4 | 84.4 | 98.0 | 94.5 | 98.3 | 92.8 |
| LSA \[1\] | 91.6 | 98.3 | 87.8 | 92.3 | 89.7 | 90.7 | 84.1 | 97.7 | 91.0 | 98.4 | 92.2 |
| DAE | 92.6 | 99.2 | 90.3 | 93.8 | 91.8 | 91.6 | 83.4 | 98.7 | 90.7 | 97.6 | 92.9 |
| ARAE | 93.7 | 99.1 | 91.1 | 94.4 | 92.3 | 91.4 | 83.6 | 98.9 | 93.9 | 97.9 | 93.6 |
Table 3: AUC and $F_1$ values for the COIL-100 dataset. The values were obtained using protocol 1 for $n \in \{1, 4, 7\}$ and different anomaly percentages.

| Method                      | OutlierPursuit | DPCP | $l_1$ thresholding | R-graph | GPND | DAE | ARAE |
|-----------------------------|----------------|------|--------------------|---------|------|-----|------|
|                            | [39]           | [33] | [30]               | [40]    | [25] |
| Normal samples: one category of images, Anomalous samples: 50% |
| AUC                         | 0.908          | 0.900| 0.991              | 0.997   | 0.968| 0.997| 0.998|
| $F_1$                       | 0.902          | 0.882| 0.978              | 0.990   | 0.979| 0.994| 0.993|
| Normal samples: four category of images, Anomalous samples: 25% |
| AUC                         | 0.837          | 0.859| 0.992              | 0.996   | 0.945| 0.990| 0.997|
| $F_1$                       | 0.686          | 0.684| 0.941              | 0.970   | 0.960| 0.950| 0.973|
| Normal samples: seven category of images, Anomalous samples: 15% |
| AUC                         | 0.822          | 0.804| 0.991              | 0.996   | 0.919| 0.986| 0.993|
| $F_1$                       | 0.528          | 0.511| 0.897              | 0.955   | 0.941| 0.901| 0.941|

Table 4: $F_1$ scores for MNIST dataset. The scores were obtained for different anomaly percentages using protocol 1 by taking the normal class as the positive one.

| Anomaly percentage | ALOCC | LOF | DRAE | GPND | DAE | ARAE |
|--------------------|-------|-----|------|------|-----|------|
|                    | [27]  | [1] | [37] | [25] |
| 10                 | 0.97  | 0.92| 0.95 | 0.983| 0.978| 0.977|
| 20                 | 0.92  | 0.83| 0.91 | 0.971| 0.959| 0.965|
| 30                 | 0.92  | 0.72| 0.88 | 0.961| 0.945| 0.95  |
| 40                 | 0.91  | 0.65| 0.82 | 0.95  | 0.926| 0.938|
| 50                 | 0.88  | 0.55| 0.73 | 0.939| 0.9  | 0.925|

Table 5: FPR for 99.5% TPR of MNIST dataset.

| Method | 0   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| DAE    | 0.089| 0.014| 0.581| 0.603| 0.565| 0.642| 0.194| 0.541| 0.902| 0.233|
| ARAE   | 0.028| 0.010| 0.562| 0.269| 0.457| 0.361| 0.070| 0.495| 0.818| 0.182|
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Fig. 3: Left: $F_1$ scores for the MNIST dataset. Right: FPR at 99.5% TPR of the MNIST dataset.

4.3 Ablation

In addition to the $\ell_\infty$ perturbation set, we consider $\ell_2$, and also rotation and translation perturbation sets. We need to solve a similar optimization to the one in Eq. 4, with the only difference being the perturbation sets [9]. Specifically, we solve this optimization problem on $\ell_2$-bounded perturbations for each sample $X \in S$ through PGD [20] again. We next solve this optimization on rotation and translation perturbation sets for each sample $X \in S$ by quantizing the parameter space, and performing a grid search on the quantized space and choosing the one with the highest latent loss. This is the most reliable approach for solving rotation and translation perturbations that is mentioned in [9]. Following the approach in [32], we use the union of these perturbation sets to make the attack even stronger to avoid as much as brittle features that models might use [15]. We present our results for MNIST in Table 6. This variant of our method is denoted as ARAE-A. Notably, the AUC is improved further in this variant in the most challenging class 8 in MNIST from 93.9 based on $\ell_\infty$ attack to 95.6 using the union of the mentioned attacks. Despite this improvement, the average AUC is still the same as in the original ARAE method.

Table 6: AUC values for the MNIST dataset. Results for other variants of our method are reported.

| Method   | 0   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | Mean |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| DAE      | 99.6| 99.9| 93.9| 93.5| 96.4| 94.3| 99.0| 95.8| 89.1| 97.5| 95.9 |
| ARAE     | 99.8| 99.9| 96.0| 97.2| 97.0| 97.4| 99.5| 96.9| 92.4| 98.5| 97.5 |
| ARAE-A   | 99.1| 99.7| 95.2| 96.7| 97.7| 98.3| 99.2| 97.1| 95.6| 96.8| 97.5 |
| ARAE-R   | 99.3| 99.9| 93.2| 92.5| 96.2| 96.6| 99.3| 97.3| 91.2| 98.2| 96.4 |

Instead of designing the attack based on the latent layer, one could directly use the reconstruction loss to do so. We denote this variant as ARAE-R. However,
we observed that a model that is robust to the latter attack yields a lower improvement compared to ARAE (see Table 6). To justify this effect, we note that an AE model that is robust based on the latter attack does not necessarily have a stable latent layer. This stems from the fact that the encoder and decoder are almost inverse functions by construction, and a destabilization of the latent encoding by an attack could be repressed by the decoder. In summary, an attack based on the latent layer is stronger than an attack based on the reconstruction error, and hence the former promotes more robust features.

5 Visualization

| Input | DAE rec. | DAE map | ARAE rec. | ARAE map |
|-------|----------|---------|-----------|----------|
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |

Fig. 4: ARAE and DAE reconstructions and saliency maps for five random inputs in MNIST dataset.

In the experiments section, we showed that our method achieves state-of-the-art results on three mentioned datasets. In order to demonstrate the reasons
behind these results, we show that ARAE learns more semantically meaningful features than DAE by interpreting these two approaches.

5.1 Interpreting with Occlusion-1

In this method, we measure the effect of each part of the input on the output, by occluding it and observing the difference in the output. Finally, we visualize these differences as a saliency map [3][4]. In the occlusion-1 method, we iteratively set each pixel to black and then observe the reconstruction error. If it increases, we set the corresponding pixel in the saliency map to blue, and otherwise set it to red. The intensity of a pixel is determined by the amount that the reconstruction error has changed. Here, we compare ARAE and DAE reconstructions and saliency maps on MNIST and Fashion-MNIST datasets.

In Fig. 4 the model has been trained on the class 8 of MNIST dataset and noisy inputs are obtained by adding a uniform noise in the interval [0, 0.4]. The outputs and saliency maps of ARAE and DAE are shown for five random inputs.
in the normal class. It is evident that DAE is focusing too much on the random noises and has a poorer reconstruction than our model.

| ARAE | DAE |
|------|-----|
| ![Image](image1.png) | ![Image](image2.png) |
| ![Image](image3.png) | ![Image](image4.png) |
| ![Image](image5.png) | ![Image](image6.png) |
| ![Image](image7.png) | ![Image](image8.png) |
| ![Image](image9.png) | ![Image](image10.png) |
| ![Image](image11.png) | ![Image](image12.png) |
| ![Image](image13.png) | ![Image](image14.png) |

Fig. 6: Local minima of inputs of ARAE and DAE, by initializing the input with a random noise and optimizing the reconstruction loss with respect to the input. ARAE produces more realistic 8 digits compared to DAE.

Similar to MNIST, we carry out the occlusion-1 method on the class dress in the Fashion-MNIST dataset. The results are shown in Fig. 5. In Fashion-MNIST, it is also obvious that random noises have a larger effect on the output of DAE. Furthermore, DAE reconstructions are less accurate than those of ARAE. These observations are consistent with the known fact that adversarial robustness can increase the model interpretability [34] by avoiding the learning of brittle features [15].

5.2 Local Minima Visualization

We expect from an ideal model that is trained on the MNIST class 8 to have lower reconstruction error as the input gets more similar to a typical 8. With this motivation, we start from a random noise and iteratively modify it in order to minimize the reconstruction error using gradient descent. The results achieved by our model and DAE are shown in Fig. 6. This figure demonstrates that inputs that lead to local minima in ARAE are much more similar to 8 than in DAE.
6 Conclusions

We introduced a variant of AE based on the robust adversarial training for novelty detection. This is motivated by the goal of learning representations of the input that are almost robust to small irrelevant adversarial changes in the input. A series of novelty detection experiments were performed to evaluate the proposed AE. Our experimental results of the proposed ARAE model show state-of-the-art performance on three publicly available datasets. This suggests that the benefits of adversarial robustness indeed go beyond security. Furthermore, by performing an ablation study, we discussed the effect of multiple perturbation sets on the model. Future work inspired by this observation could investigate the effect of other types of adversarial attacks in the proposed framework.

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