Deep Anomaly Detection by Residual Adaptation

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Abstract

Deep anomaly detection is a difficult task since, in high dimensions, it is hard to completely characterize a notion of “differentness” when given only examples of normality. In this paper we propose a novel approach to deep anomaly detection based on augmenting large pretrained networks with residual corrections that adjusts them to the task of anomaly detection. Our method gives rise to a highly parameter-efficient learning mechanism, enhances disentanglement of representations in the pretrained model, and outperforms all existing anomaly detection methods including other baselines utilizing pretrained networks. On the CIFAR-10 one-versus-rest benchmark, for example, our technique raises the state of the art from 96.1 to 99.0 mean AUC.

1 Introduction

The core goal of anomaly detection is the identification of unusual samples within data (Edgeworth 1887; Grubbs 1969; Schölkopf et al. 1999; Chandola et al. 2009). What complicates matters is that unusualness can be caused by a variety of factors, especially for data types that are semantically rich.
For these settings, there has been continued interest in developing new deep anomaly detectors (Zhai et al., 2016; Schlegl et al., 2017; Sabokrou et al., 2018; Deecke et al., 2018; Ruff et al., 2018; Golan & El-Yaniv, 2018; Pidhorskyi et al., 2018; Hendrycks et al., 2018, 2019b) that utilize end-to-end learning, a defining property amongst deep learning approaches (Krizhevsky et al., 2012; He et al., 2016).

For deep anomaly detection there is no natural learning objective, and thus several methods have been proposed. One emerging trend is to utilize self-supervision (Golan & El-Yaniv, 2018; Hendrycks et al., 2019b; Bergman & Hoshen, 2020). In these approaches one creates an auxiliary task from a nominal dataset by transforming its samples, and then utilizing these in a fashion that resembles supervision. A different approach uses large unstructured collections of data, which serve a purpose similar to outliers Hendrycks et al. (2018), to train models akin to classifiers (Ruff et al., 2020b), or enhance self-supervised learning criterions (Hendrycks et al., 2019b). Considering the rather simplistic objective for these approaches, especially compared to the richness of images, one may wonder whether they learn particularly meaningful features from such training procedures. This is potentially problematic since anomalies can manifest themselves in subtle ways that require a good semantic understanding: for example, anomalous objects may appear in crowded scenes (Mahadevan et al., 2010), or be subject to transitions between day and night in video footage (Sultani et al., 2018).

Recently there has been a large increase in the availability and utilization of pretrained networks. Ideally, these will enhance the representations learned by task-specific downstream models, as they already incorporate different variations commonly seen in data (edges, color, semantic parts, etc.). While He et al. (2019) fundamentally questioned whether actual benefits are brought about by pretrained models, Hendrycks et al. (2019a) recently painted them in a more positive light, showing they boost performance in robustness and uncertainty tasks.

Pretrained representations are relied upon in many areas of machine learning, for example in object detection (Girshick et al., 2014; Girshick, 2015), transfer learning (Guo et al., 2019), when looking to transfer between large numbers of tasks (Zamir et al., 2018), or from one domain to another (Rebuffi et al., 2017, 2018). Other examples can be found in natural language processing, where a surge of papers has recently elevated the role of pretrained models (Mikolov et al., 2018; Devlin et al., 2018; Howard & Ruder, 2018; Adhikari et al., 2019; Beltagy et al., 2019; Hendrycks et al., 2020).

While anomaly detection fundamentally differs from common pretraining tasks (e.g. ImageNet (Deng et al., 2009)) since it is more abstract and less well-defined, it may still benefit from adapting rich, pretrained representations. In doing so, one should however ensure that the change in representation is not excessive (Li et al., 2018), as this risks catastrophic forgetting (Kirkpatrick et al., 2017). For anomaly detection in particular, it is crucial to preserve variations incorporated
Figure 1: Instead of finetuning parameters of pretrained models, ADRA keeps them fixed and injects new learnable connections into the network (symbolized in blue). Extending the model with new parameters lets ADRA incorporate representations suitable for deep anomaly detection, while holding on to information incorporated in the pretraining task. Best viewed in color.

during pretraining that, even though they potentially don’t exist in the training set, can nonetheless be meaningful for inferring anomalous characteristics at test time. On the other hand, it is important to let the network have some flexibility to learn new variations which are important for the new task.

In this paper we introduce an anomaly detection method that goes beyond the traditional finetuning paradigm by using lightweight dynamic enhancements (Decke et al., 2020), which serve as modifications to the pretrained network at every layer; for a visualization, see Figure 1. We call this anomaly detection with residual adaptation (ADRA). This introduces a simple enhanced objective that combines outlier exposure (Hendrycks et al., 2018) and deep one-class classification (Ruff et al., 2020a), two powerful learning techniques for anomaly detection. ADRA is straightforward to train and deploy, highly parameter-efficient, and can much better consolidate pretrained networks and anomaly detection than mere feature extraction (Bergman et al., 2020). In extensive experiments we show that ADRA outperforms all previous approaches in the deep anomaly detection literature on a set of common benchmarks. On the CIFAR-10 one-versus-rest benchmark, for example, our technique raises the state of the art from 96.1 to 99.0 mean AUC, reducing the gap to perfect performance by 75%. Besides the strong performance of ADRA, we use images from a new disentanglement dataset (Gondal et al., 2019) to show that ADRA naturally disentangles meaningful variations in data into its representations.

2 Related work

Anomaly detection has a long history, with early work going back to Edgeworth (1887) and has been extensively studied in the classical machine learning literature, e.g. through generative models for intrusion detection (Yeung & Chow, 2002), or hidden Markov models for registering network attacks (Ourston et al., 2003). Other examples include active learning of anomalies (Pelleg & Moore,
or dynamic Bayesian networks for traffic incident detection (Singh & Hauskrecht, 2006). An overview of traditional anomaly detection methods can be found in Chandola et al. (2009), an empirical evaluation in Emmott et al. (2013).

Previous deep anomaly detection methods utilized autoencoders (Zhou & Paffenroth, 2017; Zong et al., 2018), hybrid methods (Erfani et al., 2016), or generative adversarial networks (Schlegl et al., 2017; Akcay et al., 2018; Deecke et al., 2018; Perera et al., 2019). A recent focus is on repurposing auxiliary tasks for anomaly detection, often following the paradigm of self-supervision: Golan & El-Yaniv (2018) propose learning features from predicting geometric transformations of the nominal data, which was extended to other data types by Bergman & Hoshen (2020). In a separate line of work, Hendrycks et al. (2018) propose carrying out anomaly detection through a paradigm they call outlier exposure where one utilizes large unstructured sets of data, assumed to not belong to the normal class, to improve performance of deep anomaly detection. Our approach also leverages learning from such corpora, however bypasses all self-supervision steps entirely.

The technique of adding residual connections to adapt networks to new tasks, also known as residual adaptation, was introduced in Rebuffi et al. (2017, 2018). While originally developed for multi-task learning, this assumption was recently relaxed in work that extended residual adaptation to other problem settings, such as latent domain learning (Deecke et al., 2020). In the realm of language modeling, Stickland & Murray (2019) applied residual adaptations to pretrained BERT networks (Devlin et al., 2018) to improve performance there. Our method further demonstrates the usefulness of residual adaptation outside of multi-task learning by extending it to the task of anomaly detection.

A number of recent publications proposed unsupervised mechanisms to learn disentangled representations (Kulkarni et al., 2015; Higgins et al., 2017; Bouchacourt et al., 2018; Burgess et al., 2018; Chen et al., 2018; Kim & Mnih, 2018; Kumar et al., 2018). Locatello et al. (2019) outlined the incompatibility of unsupervised learning and representation disentanglement, and follow-up work established the need for some form of weak supervision to give rise to disentanglement (Locatello et al., 2020). Considerable hopes have been placed on the usefulness of such disentangled representations (Bengio, 2017; van Steenkiste et al., 2019). We investigate connections to anomaly detection in Section 4.4.

## 3 Method

We review the individual components to our proposed approach in Sections 3.1 and 3.2 then subsequently introduce ADRA in Section 3.3.
3.1 Deep one-class classification

When learning from data, a semantic understanding of normality is typically extracted from a set of data $S_n = \{x_j\}_{j=1}^n$ assumed to have been sampled i.i.d. from the nominal distribution $\mathbb{P}$ over some sample space $\mathcal{X}$. How this data is then incorporated is how the different approaches in the anomaly detection literature can be categorized, e.g. in an unsupervised way (Ruff et al., 2018), or through self-supervision (Golan & El-Yaniv 2018, c.f. Section 2). The ansatz of outlier exposure (Hendrycks et al., 2018) revolves around the utilization of a large number of unlabeled images from some unstructured corpus of data $Q_m$ (where potentially $m \gg n$), for example 80 Million Tiny Images (Torralba et al., 2008), on which models are trained to identify whether samples belong to the corpus, or the nominal data. Importantly, this is a form of weak supervision via existing resources (Zhou, 2018), and not equivalent to binary classification: images from the corpus are not necessarily outliers (and may even contain samples from $\mathbb{P}$). Nonetheless, this procedure can help models incorporate richer representations of the data in $S_n$.

Initially observed in Ruff et al. (2020b), the structure of anomaly detection tasks benefits from encapsulating the normal class through radial functions, in line with the so-called concentration assumption fundamental in anomaly detection (Schölkopf & Smola, 2002; Steinwart et al., 2005). Ruff et al. (2020a) showed that outlier exposure also benefits from a reformulation via a class of spherical learning objectives, which the authors use to set the current state of the art in anomaly detection performance. Given access to data, this learning criterion can be expressed as a functional of some model $f$ as

$$\mathcal{H}[f] = \frac{1}{N} \sum_{i=1}^{N} y_i h(f(x_i)) + (1 - y_i) \log \{1 - \exp(-h(f(x_i)))\},$$

(1)

where pseudo-labels $y_i$ are determined by a sample’s origin, i.e. $y(x_i) = 1_{x_i \in Q_m}$. This loss can be coupled with different radial functions $h$, which Ruff et al. (2020a) recommend setting to $h(f(x)) = \sqrt{\|f(x)\|^2 + 1} - 1$. We follow their recommendation in this work, and found it to be stable across experiments.

Note that previous works (to which we compare in our experiments, see Section 4) would use some randomly initialized neural network and obtain its parameterization via minimization of some criterion, in the above case for example $\theta = \arg \min_{\theta'} \mathcal{H}[f_{\theta'}]$. In ADRA, we constrain the optimization to a more suitably regularized class of functions, see Section 3.3.

3.2 Residual adaptation

In conventional residual networks (He et al., 2016), the information from the $l$’th layer is passed on via $x_{l+1} = x_l + f_{\theta_l}(x_l)$, where each $f_{\theta_l}$ is typically parameter-
ized as a 3x3 convolution. Originally developed in the context of multi-domain learning, Rebuffi et al. (2018) proposed adding a small linear correction to every layer, such that
\[ x_{l+1} = x_l + f_{\theta_l}(x) + h_{\alpha_l}(x), \] (2)
with each \( h_{\alpha_l} \) parameterized by a smaller 1x1 convolution. Deecke et al. (2020) recently generalized this concept through a mixture of experts approach. For this, a set of \( K \) linear corrections \( \{ h_{\alpha_k} \}_{k=1}^{K} \) is introduced at every layer, which are targeted via a self-attention mechanism \( g_k \) that adaptively combines available corrections. This yields
\[ x_{l+1} = x_l + f_{\theta_l}(x) + \sum_{k=1}^{K} g_k(x)h_{\alpha_k}(x). \] (3)

As the authors show, residual adaptation gives rise to an efficient plug-in module that encourages parameter sharing between similar modes in data. Crucially, the module also increases the robustness of models in regions where the density associated with the data-generating distribution has little mass — regions of particular importance to anomaly detection.

The motivation behind residual adaptation was developed in earlier work on universal representations (Bilen & Vedaldi, 2017). At their core, universal representations build on the idea that general-purpose parameters obtained through some large pretraining task require only small modifications for them to be adapted to a wide range of tasks. Even though universal representations were originally conceived with the objective of training compact models over sets of very different tasks, our experiments suggest that its insights hold promise for a wider range of learning problems, anomaly detection included.

### 3.3 Anomaly detection with residual adaptation

Following work that investigated the prospects of large pretrained networks (Devlin et al., 2018; Howard & Ruder, 2018; Adhikari et al., 2019; Beltagy et al., 2019; Hendrycks et al., 2020), a recent study proposed carrying out anomaly detection through a nearest neighbor search on top of features extracted from a large pretrained residual network (Bergman et al., 2020). We include this approach in our experiments (see Table 1), but as its performance shows, simply transferring over fixed representations to an unrelated task does not sufficiently incorporate abstract information, limiting its usefulness for complex, high-dimensional anomaly detection. Next, we outline how parameters obtained from pretraining can be more adequately repurposed for a new task.

The initial pretraining itself follows a simple protocol: a model’s parameters are randomly initialized from some distribution over parameters (for example Xavier

\[ \text{This omits normalization and activation to declutter notation.} \]
initialization (Glorot & Bengio, 2010)). Minimization of a suitable pretraining task $A$ (say, object classification on ImageNet (Deng et al., 2009)) then yields a set of general-purpose parameters $\theta$. The so-obtained model $f_\theta$ is now fully “pretrained”, ready to be used in a downstream task $B$.

The traditional ansatz for leveraging pretrained models is to “finetune”, i.e. continuing to optimize the model parameters (or a subset thereof) on $B$. Finetuning can therefore be seen as a type of weight initialization, using weights from a pretrained network. One crucial limitation of this learning protocol is that when learning on $B$ isn’t carried out very carefully through the introduction of some explicit inductive bias (Li et al., 2018), this risks catastrophic forgetting of information previously extracted from $A$. To alleviate this a common approach is to develop adequate forms of regularization, which were used successfully e.g. in continual learning (Kirkpatrick et al., 2017; Lopez-Paz & Ranzato, 2017). The explicit bias we introduce in ADRA is different, and instead obtained by sidestepping the standard finetuning protocol and directly modifying the model’s structure.

To modulate the base network, ADRA introduces a fresh set of model parameters $\alpha \sim \mathbb{P}_\alpha$. These have not previously been exposed to the pretraining task $A$, and serve to incorporate the task-specific variations crucial to inferring anomaly. At the same time, ADRA fixes the pretrained parameters and never changes them, which ensures they remain linked to the information obtained in $A$. In doing so, our methodology constraints the learning criterion, recasting the optimization of the radial loss functional introduced in eq. (1) as

$$f_{\theta\alpha} = \arg\min_{\alpha'} \mathcal{H}[f_{\theta\alpha'}], \quad \text{s.t. } \theta = \arg\min_{\theta'} \mathcal{A}[f_{\theta'}].$$

(4)

Because the pretrained parameters $\theta$ are fully determined via $A$ and fixed thereafter, only the new set of residual connections $\alpha$ is task-specific. For every nominal class, ADRA therefore only requires the parameters specific to $\mathbb{P}$ to be inserted back into the model. This requires a much smaller number of overall model parameters (i.e. $|\alpha| \ll |\theta|$), giving rise to a highly efficient, adaptive architecture $f_{\theta\alpha}$.

4 Experiments

We consider three settings to evaluate our method: anomaly detection on the (i.) one-versus-rest and (ii.) hold-one-out benchmarks, as well as (iii.) measuring the disentanglement of learned representations. All experiments use code implemented through standard routines in PyTorch (Paszke et al., 2017).
4.1 One-versus-rest anomaly detection

We evaluate performance of ADRA on the CIFAR-10 (Krizhevsky & Hinton, 2009) one-versus-rest anomaly detection benchmark, which is reported across large parts of the literature (Deecke et al., 2018; Golan & El-Yaniv, 2018; Hendrycks et al., 2018; Ruff et al., 2018; Abati et al., 2019; Hendrycks et al., 2019b; Perera et al., 2019; Bergman & Hoshen, 2020; Ruff et al., 2020a,b). This benchmark is not equivalent to CIFAR-10 classification, and consists of ten individual tasks instead: in each, a single class $y_c$ is fixed as the normal class—say, dogs. All dogs in the CIFAR-10 training split are collected into $S_n$, from which models can then be learned about the nominal distribution $P_{y_c}$. Finally, models are evaluated against the entire CIFAR-10 test split, and performance is recorded by checking whether anomaly scores assigned to dogs are lower than scores assigned to the remaining non-dog classes. To express performance through a single number, authors usually report AUC under the receiver operating characteristic; we follow this practice here.

In ADRA, we additionally contrast $S_n$ against images from an unstructured corpus $Q_m$. Guided by previous work (Hendrycks et al., 2018; Ruff et al., 2020a), we fix this to contain all samples from the CIFAR-100 training split. Access to $Q_m$ should best be thought of as a weak supervisory signal: CIFAR-100 does not contain any of the classes in CIFAR-10, so 9 out of 10 classes are only seen during evaluation, making them true outliers.

**Optimization** Training is carried out using stochastic gradient descent (momentum parameter of 0.9, weight decay of $10^{-4}$) for a total of 120 epochs, with learning rate reductions by $1/10$ after 80 and 100 epochs. The batch size is fixed to 128, with each batch containing an equivalent number of samples from $S_n$ and $Q_m$. All experiments use a residual network with 26 layers, and unless otherwise noted, its initial parameters were obtained from pretraining on a downsized ImageNet variant (at 72x72 resolution), for a final top-1 accuracy of 60.32%. ADRA parameters $\alpha$ are always initialized randomly, and then trained on the constrained objective in eq. (4). We vary the number of linear corrections in ADRA over $K = \{1, 2, 4\}$. Performances for ADRA are recorded by averaging over five random initializations.

**Results** As shown in Table 1, ADRA raises the state of the art to 99.0 mean AUC, closing the gap between the previous best method of 96.1 mean AUC (SAD (Ruff et al., 2020a)) and perfect classification by roughly 75%. As demonstrated by the performance of kNN-AD (Bergman et al., 2020), a different work also focusing on the utilization of pretrained networks for anomaly detection, simply using features from a large pretrained network alone does not solve the problem of detecting anomalies. Our results suggest including adaptation in a proper way is critical for utilizing these networks to their full potential.
| Class | GT   | IT  | kNN-AD | GT+   | SAD | $K = 1$ | $K = 2$ | $K = 4$ |
|-------|------|-----|--------|-------|-----|--------|--------|--------|
| 0     | 74.7 | 78.5| 93.9   | 90.4  | 96.4| 98.8   | 99.0   | 99.1   |
| 1     | 95.7 | 89.8| 97.7   | 99.3  | 98.8| 99.7   | 99.8   | 99.8   |
| 2     | 78.1 | 86.1| 85.5   | 93.7  | 93.0| 96.3   | 98.1   | 98.6   |
| 3     | 72.4 | 77.4| 85.5   | 88.1  | 90.0| 95.7   | 96.3   | 97.3   |
| 4     | 87.8 | 90.5| 93.6   | 97.4  | 97.1| 98.2   | 98.1   | 98.2   |
| 5     | 87.8 | 84.5| 91.3   | 94.3  | 94.2| 97.4   | 98.1   | 98.2   |
| 6     | 83.4 | 89.2| 94.3   | 97.1  | 98.0| 99.4   | 99.6   | 99.6   |
| 7     | 95.5 | 92.9| 93.6   | 98.8  | 97.6| 99.1   | 99.5   | 99.5   |
| 8     | 93.3 | 92.0| 95.1   | 98.7  | 98.1| 99.4   | 99.4   | 99.5   |
| 9     | 91.3 | 85.5| 95.3   | 98.5  | 97.7| 99.1   | 99.4   | 99.3   |

Mean AUC 86.0 86.6 92.5 95.6 96.1 98.3 98.8 99.0

Dynamic residual adaptation with self-attention as proposed by Deecke et al. (2020) improves performance across the benchmark. For larger $K$, the improvement in effectiveness is reduced, as sufficient adaptivity is likely already obtained for a smaller number of experts. Unless otherwise noted, in subsequent trials we therefore fix $K = 2$.

Current existing methods require that all parameters of each model are stored. This scales their memory requirements as $O(T\|\theta\|)$, where $T$ denotes the number of subtasks (e.g. ten for our benchmarks). For ADRA, a small set of task-specific corrections augment the base model, reducing its computational footprint to $O(\|\theta\| + KT\|\alpha\|)$. On our benchmarks for example, ADRA with $K = 2$ requires only around 20.2mil parameters in total, a fraction of the roughly 62.1mil parameters required to parameterize ten individual ResNet26. We visualize these savings in Figure 3 (left).

### 4.2 Robustness to small modes

Ideally models have the ability to incorporate information from nominal samples even if they form only a minor mode of $\mathbb{P}$, such that only few samples from this mode are contained in $S_n$. Deecke et al. (2020) suggest that dynamic residual adaptation benefits the robustness to small latent domains, i.e. regions where the density associated with the data-generating distribution has little mass. Next, we evaluate this property in the context of anomaly detection.

For this experiment, we let the normal class be constituted by samples associated with pairs of classes $(y_a, y_b)$, such that $S_n \sim \mathbb{P}_{y_a} + r\mathbb{P}_{y_b}$, with $r \in [0, 1]$ controlling the presence of samples from $y_b$. For a robust model, even as $\mathbb{P}$ is relaxed toward
Figure 2: Relative AUCs for the secondary class for pairs of classes from CIFAR-10. Shown are performances for a random initialization (●), traditional finetuning (●), and ADRA (●). Dashed curves indicate the relative change in performance for the primary class.

$P_{y_a}$, its ability to detect normality amongst the secondary class remains intact.

We pair up classes from CIFAR-10, and report AUCs relative to $r = 1$ for the primary and secondary class in Figure 2. When models are trained from a random initialization, their performance falls of faster than for approaches that start from pretrained networks. This trend is consistent across class pairings. There is a modest increase in performance for traditional finetuning, ADRA offers the highest robustness at incorporating small nominal modes.

### 4.3 Hold-one-out anomaly detection

An alternative benchmark implemented in Perera et al. (2019) or Ahmed & Courville (2019) is to collect multiple classes into the nominal data $S_n$, while only a single class is declared anomalous and set aside during training. At test time then, the task is to identify samples from the held-out class. It has been argued that this is a more difficult benchmark than one-versus-rest, since it requires the learning of multiple nominal modes (Ahmed & Courville, 2019; Bergman et al., 2020).

On the hold-one-out benchmark, Ahmed & Courville (2019) evaluate the performance of ranking anomaly via maximum softmax probability (Hendrycks & Gimpel, 2017) and ODIN (Liang et al., 2018) in combination with an auxiliary self-supervised criterion inspired by RotNet (Gidaris et al., 2018). In particular, the authors propose evaluating models on STL-10 (Coates et al., 2011) for a novel, more difficult benchmark: its images have a higher resolution of 96x96, while only containing 500 samples for each object class. The dataset also contains a large unlabeled split, which we collect into our corpus $Q_m$ for outlier exposure.
Table 2: Average precisions on CIFAR-10 and STL-10 hold-one-out benchmarks. ADRA uses $K = 2$.

| Class | CIFAR-10 | STL-10 |
|-------|----------|--------|
|       | RA-ODIN  | TF     | L^2-SP | ADRA  | RA-ODIN | TF     | L^2-SP | ADRA  |
| 0     | 49.8     | 43.0   | 50.8   | 42.9  | 23.1    | 23.1   | 44.5   | 43.1  |
| 1     | 17.4     | 76.7   | 77.4   | 88.4  | 40.1    | 13.8   | 14.8   | 23.7  |
| 2     | 54.6     | 61.1   | 68.0   | 74.4  | 16.9    | 39.9   | 82.2   | 56.0  |
| 3     | 55.8     | 65.8   | 72.7   | 72.5  | 31.4    | 18.9   | 27.4   | 37.5  |
| 4     | 52.8     | 60.6   | 65.3   | 73.3  | 29.7    | 25.3   | 17.0   | 28.8  |
| 5     | 32.5     | 64.2   | 65.1   | 63.3  | 26.1    | 17.3   | 12.3   | 18.5  |
| 6     | 54.4     | 84.0   | 89.9   | 90.7  | 23.6    | 30.1   | 22.1   | 33.5  |
| 7     | 39.7     | 52.9   | 46.8   | 53.2  | 28.3    | 18.4   | 14.9   | 44.2  |
| 8     | 28.8     | 70.8   | 64.2   | 74.4  | 15.4    | 49.2   | 70.3   | 59.4  |
| 9     | 29.9     | 87.7   | 84.5   | 94.1  | 16.6    | 40.7   | 44.4   | 55.7  |

Mean AP

| Class | CIFAR-10 | STL-10 |
|-------|----------|--------|
|       | RA-ODIN  | TF     | L^2-SP | ADRA  | RA-ODIN | TF     | L^2-SP | ADRA  |
| 0     | 72.7     | 25.1   | 27.7   | 35.0  | 40.0    |

For STL-10, we pretrained ResNet26 for a final top-1 classification accuracy of 63.74% on ImageNet at this resolution. All other optimization settings remain unchanged from those outlined in Section 4.1.

Results

We follow Ahmed & Courville (2019) and report performance on the hold-one-out benchmark in terms of average precision. We include their best results, rotation-augmented ODIN (RA-ODIN), in Table 2. We do not include the results for OCGAN from Perera et al. (2019) in our tabulation, as the authors report in AUC instead. Note however ADRA outperforms OCGAN on mean AUC by a wide margin: 94.7 versus 65.7.

As our results confirm, inferring anomaly on STL-10 is significantly harder. In particular, traditional finetuning (TF) does not successfully address the task of anomaly detection, likely because variations that are important to determining anomaly at test time are overwritten in the finetuning process, yielding poor performance across classes (mean AP of 27.7). To counteract this, we follow the recommendation of Li et al. (2018) and add a penalty toward the initial pretrained parameters via L^2-SP regularization, scaled with a regularization strength of $\alpha = 10^{-2}$. While this boosts performance somewhat (mean AP of 35.0), simply regularizing the otherwise unchanged finetuning process does not fully address the issue of forgetting information extracted during pretraining.

By modifying the structure of the base model, ADRA introduces a different explicit bias toward the initial pretrained representation. Our results indicate that preserving the initial pretrained parameters and adapting the network to the task through the introduction of new network components allows one to keep both the benefits of pretraining and learning for a specific task.
4.4 Disentanglement of representations

![Figure 3: Left: memory requirements for incorporating ten tasks, just as in our benchmarks. ADRA combines parameters of a single pretrained base model (•) with task-specific corrections (•), giving rise to a lean overall model (•) that incurs large savings compared to SAD (•) and other previous methods. Calculation shown for K = 2. Right: DCI disentanglement for different methods, both unsupervised (SVDD, UADRA) and using weak supervision through outlier exposure (TF, L²-SP, SAD, ADRA).](image)

Next, we take a closer look at the representations learned by different anomaly detection methods. For this, we examine models on MPI3D [Gondal et al., 2019], a recently released dataset to facilitate research on disentangled representations. It contains joint pairs of ground-truth factors $z$ (color, shape, angle, etc.), and corresponding images $x$ of a robot arm mounted with an object. The original dataset comes in three different styles (photo-realistic, simple or detailed animation); we only make use of the more complex, photo-realistic images here.

We compare ADRA to two fundamental approaches to deep anomaly detection: deep SVDD, a fully unsupervised one-class model proposed in [Ruff et al., 2018], and SAD [Ruff et al., 2020b,a], which can be viewed as a direct extension of SVDD that additionally incorporates outlier exposure into the learning criterion. Moreover, we include traditional finetuning (TF) and finetuning with regularization (L²-SP [Li et al., 2018]), both trained with outlier exposure. To ablate against weak supervision, we also train our method in an unsupervised fashion (UADRA), i.e. with an empty corpus $Q_m = \emptyset$.

For our experiments on MPI3D, we arbitrarily fix a red cone as the normal object, and then train models on all available views. For methods that use outlier exposure, we include all such images that do not constitute the normal class. For example $z_{\text{color}} = \{\text{white, green, blue, brown, olive}\}$ all appear in the corpus $Q_m$. For ADRA, we can simply reuse the pretrained network also used in our CIFAR-10 benchmarks, and otherwise leave the optimization protocol unchanged from that in Section 4.1. To measure disentanglement, we follow [Locatello et al., 2020] and evaluate models in terms of DCI disentanglement [Eastwood & Williams, 2018].
Results

Disentanglement is often a desirable property (Bengio, 2017; van Steenkiste et al., 2019). Representations learned via SVDD, i.e., unsupervised anomaly detection, however exhibit relatively little of it (see Figure 3, right). Outlier exposure as in SAD raises disentanglement. This is in line with observations in Locatello et al. (2020), which showed that some weak supervision is required for learning disentangled representations.

ADRA exhibits the highest amount of disentanglement in its representations. To ensure that this actually stems from our model, we ablate this against UADRA. Removing access to the weak supervision of \( Q_m \) causes another anticipated loss in disentanglement, but UADRA still disentangles better than SVDD. So while both our model and outlier exposure increase DCI disentanglement, their benefits should be viewed as distinct.

Interestingly TF and L2-SP perform much worse than SAD, even though they only differ in their in parameter initialization. This is potentially because the pretrained network weights aren’t particularly well suited for the task, and the dataset size is too small in proportion to the number of free parameters to adapt them. ADRA on the other has a much smaller number of free parameters, thus allowing for sample-efficient utilization of those features which are useful from the pretrained network.

5 Conclusion

Detecting anomalies is a difficult task, especially when carried out in high-dimensional spaces. In this paper, we introduced a powerful and simple method for deep anomaly detection. By incorporating dynamic residual adaptation to leverage pretrained models, ADRA constitutes a parameter-efficient learning protocol.

Our method exhibits strong performance across common benchmarks for deep anomaly detection, and can robustly incorporate small modes of nominal data. Moreover, we established a positive link between the best performing methods for anomaly detection and their disentanglement, indicating that deep anomaly detection can directly benefit from the ongoing development of disentangled representations.

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