**ABSTRACT**

In complex industrial systems, the number of possible fault types is uncountable, making it impossible to train supervised models covering them all. Instead, anomaly detectors are trained on healthy operating condition data and raise an alarm when the data deviate from the healthy conditions, indicating the possible occurrence of faults.

Data-driven anomaly detection performance relies on a representative collection of samples of the normal (healthy) class distribution. This means that the samples used to train the model should be sufficient in number and distributed so as to empirically determine the full healthy distribution. But for industrial systems in gradually varying environments or subject to changing usage, acquiring such a comprehensive set of samples would require a long collection period and delay the point at which the anomaly detector could be trained and operational.

In this paper, we propose a framework for the transfer of complementary operating conditions between different units, to train more robust anomaly detectors. The domain shift due to different units specificities needs to be accounted for. This problem is an extension of Unsupervised Domain Adaptation to the one-class classification task. We solve the problem with adversarial deep learning and replace the traditional classification loss, unavailable in one-class problems, with a new loss inspired by a dimensionality reduction tool. This loss enforces the conservation of the inherent variability of each dataset while the adversarial architecture ensures the alignment of the distributions, hence correcting the domain shift. We demonstrate the benefit of this approach using three open source datasets.

**Keywords** Anomaly Detection, Fault detection, Unsupervised Domain Adaptation, Aircraft, Bearings, Image Processing.

**1 Introduction**

The competitiveness of safety-critical and complex industrial systems stems from the operators’ ability to provide a high-quality service at the most competitive price. As the service is contractual and regulations impose a given level of required safety, reducing the operating costs is often the only lever left. Maintenance usually accounts for a large part of these operating costs as it ensures safe and continuous operation. Preventive maintenance relies on schedules, based on known component lifetimes, and is performed more often than necessary in order to minimise the risk of failure. Switching to maintenance based on the present condition of the machine would greatly reduce unnecessary maintenance and its associated costs. Monitoring the condition of complex industrial systems requires the simultaneous monitoring of several signals, either comparing them to a physical model of the system when available, or applying intelligent data-driven approaches developed on the historic condition monitoring (CM) data recorded on the system.

The design of data-driven health monitoring approaches relies on the assumption that condition monitoring data collected in the past are representative of all the possible operating conditions and fault modes the system will face in
the future. In other words, the data used for training are assumed to be representative of all the system conditions to which the model will be applied (or tested) in the future. The requirements for good model performance are, first, that the training data originate from the same distribution as the test data, and second, that the training data are sufficient to empirically determine the test distribution.

However, this assumption often does not hold for real applications. For complex industrial systems, the collected CM data is often not representative 1) of all possible faults and 2) of all future operating conditions. First, these systems have a large number of parts and components interacting with each other, making the number of possible faults uncountable, particularly when considering that the same fault in different operating conditions may have very different consequences and may be represented by very different signatures in the CM data. Furthermore, fault occurrences are rare since, typically, these systems are reliable by design and regularly maintained. Therefore, it is hardly possible to collect enough CM data on every possible fault signature. Since learning the fault signatures is not possible, the monitoring can be performed as an anomaly detection task [20], whereby a model is trained to recognise data from healthy operating conditions only, raising an alarm when the test data are sufficiently different from those seen in training.

Second, during their lifetimes, these systems will experience changes in environmental conditions, in hardware or in operating requirements. These changes impact the collected CM data and their distributions. This can be the case, for example, for a plane changing from medium-haul to short-haul flights, or for power plants operating in an environment with strong seasonality [18]. Anomaly detection models trained on data that are not representative of the testing dataset will raise alarms upon encountering new operating conditions and thus experience a significant performance drop in their ability to detect anomalies [19]. A sufficiently lengthy data collection period might eventually cover most of the possible conditions experienced by the system. However, the delay entailed by such a long data collection period might be unacceptable for the operator.

One way of integrating more representative operating conditions into the anomaly detection model is to transfer data from other units in order to benefit from the complementary operating conditions that they have experienced. But differences in system configurations, system characteristics, or usage of the individual systems might result in different data distributions, known as a “domain shift”. Combining data from units with a domain shift will result in a performance drop unless the shift is accounted for. Previous works have devised ways to find units within a fleet with minimum domain shift [2, 19]; yet these approaches severely restrict which units can be combined, de facto limiting their application to cases with large fleets of units. Other works have focused on developing models robust to domain shifts. This task is denoted in the literature as “Domain Adaptation” or “Domain Alignment” (DA) [26, 23].

Several approaches have been proposed for domain adaptation. It often consists in devising a new feature space, or learning a new latent space, such that the units’ distributions become as similar as possible. In particular, deep domain adaptation methods embed domain adaptation within the framework of deep learning to learn more transferable representations. DA has mostly been explored for classification tasks, where the domain shift is corrected by ensuring that classes common to both units overlap in the latent space. Therefore, when correcting for the domain shift, the class labels act as anchors to conserve the intra-domain variability, containing the class discriminating information. Previous works have shown that a lack of anchoring information when performing the adaptation might lead to sub-optimal alignment [29]. Recently, adversarial domain adaptation [9, 28, 29] has shown promising results, also in cases where the class labels are not available for one unit at training time, a scenario denoted as “unsupervised domain adaptation”.

In this paper, we formalise and propose a solution to a new domain adaptation task, specifically for unsupervised anomaly detection tasks, as illustrated in Figure 2. In this domain adaptation task, we assume that none of the datasets used for training have samples of the types of anomalies that will have to be detected in the test datasets. We assume, however, that both training datasets contain data collected from different units, in healthy but not necessarily similar operating conditions, and that they may be complementary. To perform the adaptation between two units, we use an adversarial deep learning architecture and demonstrate that we can compensate for the lack of labels, traditionally used to structure the data through the back-propagation of a classification loss, with a new loss computed directly in the feature space and inspired by multidimensional scaling [6], a dimension reduction tool. This loss enforces the conservation of inter-sample relationships for each dataset and thereby preserves the inherent variability within each dataset due to the different operating conditions.

We test the proposed approach on three open datasets of varied nature. First, we apply the methodology to vibration data from bearings under different loads, the Case Western Reserve University bearing dataset [25]. The anomaly detection task is the detection of any faults present in the dataset and the domain adaptation aims to perform the adaptation from one load to another. Second, we apply the methodology to the monitoring of turbofan engines in operation, simulated using the AGTF-30 model with real flight profiles. In this case, the anomaly detection task is the detection of performance degradation in the fan, as well as in the high- and low-pressure turbines efficiency and capacity. The
Figure 1: **Domain Adaptation for Anomaly Detection**. Condition Monitoring (CM) data are collected on each unit from a fleet. Due to each unit’s characteristics and environmental conditions, the data belong to different distributions, a phenomenon known as “Domain Shift”. Alignment is performed with the proposed ADAU approach using healthy CM data only (blue triangles and green stars). The final monitoring system is able to detect anomalies.

The domain adaptation task is the alignment between two flights with different engine characteristics and different profiles. Last, to show the generalisability of the proposed approach, we demonstrate that it also provides benefits for anomaly detection in a computer vision task: the handwritten digit MNIST to MNIST-M domain adaptation task. For the anomaly detection setup, one digit is regarded as the main class and all other digits as anomalies.

The remainder of this paper is organised as follows: Section 2 presents relevant works found in the literature. Section 3 details the architecture used in this work and the new proposed loss. Last, Section 4 presents the three experiments and their results.

## 2 Related Work

The problem of domain alignment (DA) consists in solving the same machine learning task for at least two datasets with similar data characteristics but from different origins [26, 23]. In this context, the goal is usually aimed at learning to solve the task on a dataset with little information (i.e., few training samples, few or no labels), denoted as the “target” dataset, using datasets with more information, denoted as “source”. In the context of industrial systems, this could be data collected on a fleet of systems originating from the same manufacturer, and thus monitored by similar sensors [13], but experiencing a domain shift due to differences in system configuration, usage, or environment. For example, one could seek to train a diagnostics model for a wind turbine on which faults have never been observed using the data from another turbine that has been running for a longer period, possibly located on a different farm with different environmental and wind conditions [16].

The complexity of the domain adaptation challenge depends significantly on the degree of supervision available and on the quantity of collected data. Both source and target might have labeled, partially labeled, or non-labeled training datasets. Similarly, both can have more, fewer, or no data for some conditions or classes. A comprehensive review of the different cases can be found in [26, 23].

In most examples from the literature, at least the source dataset has labeled data, and mainly two scenarios are tackled in the existing research. If at training time both source and target have labeled data, the task is denoted as “supervised domain adaptation”. If the source has labeled data and the target has unlabeled data, the task is usually denoted as “unsupervised domain adaptation”; although the classification task can still be trained in a supervised manner for the source dataset. In this case, the alignment of the two datasets is a two-objective process: first, obtaining features that
Figure 2: Adversarial Domain Adaptation for Unsupervised Anomaly Detection (ADAU). The feature extractor $N_1$ is trained to minimise the multidimensional scaling loss $L_F$ and to maximise the domain discriminator loss $L_D$. The domain discriminator $N_2$ is a traditional feed-forward dense classifier. Once trained, features are fed to the one-class classifier for anomaly detection.

are independent of the dataset of origin and, second, obtaining features that are informative for the available labels of the source dataset. This can be framed as a sequential approach by first learning the best features in the source and then adapting the target features to match the source by means of a transformation [8, 31, 34]. Both tasks can also be combined into a single problem by solving a min-max problem so as to minimise the classification loss in the source domain while maximising the feature distribution overlap (or minimising a distribution distance measure) between the datasets [4].

Recently, with the rise of deep learning, several approaches have brought significant improvements to the domain adaptation problem, in particular due to the success of adversarial architectures [1, 9]. These architectures usually consist in the optimisation of a neural network in three parts: a feature encoder performing the data transformation; a feature processor, trained to solve the machine learning task of interest on the source domain (in most cases a classifier); and a feature discriminator, trained to distinguish whether the data originate from the source or target dataset. The min-max problem is solved at the level of the feature extractor. It is trained at the same time to minimise the loss of the feature processor and to maximise the discrimination loss of the discriminator. In other words, once trained, the feature extractor should provide features that are relevant for the machine learning task at hand and indistinguishable between source and target. Adversarial architectures have been implemented in several studies, performing well on the machine learning task tested on the target domain [26].

In industrial applications, domain adaptation proves useful in several contexts such as fleet monitoring [18, 21] and simulated-to-real system adaptation [32]. Domain adaptation has been mostly used for fault diagnostics [28, 29, 32, 11, 10, 24] and remaining useful life estimation [33, 7], yet it has not been studied in the context of unsupervised fault detection, apart from the preliminary studies of this work [18].

3 Method

3.1 The Network

In this paper, we propose the use of an adversarial deep learning architecture in three parts, as illustrated in Figure 1 [9, 28, 29]. It consists of a feature encoder $N_1$, an adversarial feature domain discriminator connected to the network $N_1$ with a Gradient Reversal Layer [9], and a feature processor $N_3$ performing machine learning tasks of interest (here the anomaly detection). Therefore, instead of a traditional classifier, we use a one-class classifier as feature processor $N_3$. The focus of the paper is on the alignment strategy, and on its impact on the anomaly detector performance. We perform the anomaly detection using Extreme Learning Machines since it has proven to be a simple yet efficient approach [20] that can be easily integrated within a deep learning architecture.

Usually in DA, source labels are used to ensure that the extracted features from $N_1$ are meaningful for the task at hand [29], most often a classification task. In such setups, the feature extractor is trained to minimise the classification loss for samples with labels while simultaneously maximising the domain discriminator loss between source and target.
domain. As such, the labels act as anchors during the transformation of the data, making sure that the features retain discriminant characteristics for the feature processor. For the purpose of anomaly detection as defined in our work, however, the task is unsupervised: the aim is to detect anomalies examples of which are not available at training time, neither in the source nor in the target domain. We assume, however, that a healthy set is available at the time of training for both the source and the target, albeit with very few samples for the target. The objective, therefore, is to devise domain-independent features that enable to discriminate between anomalies and the healthy class in the target data, including modes not seen during training.

To perform the feature alignment without labels, we seek to ensure that the features are meaningful with respect to the information the data originally contained. Therefore, we propose to minimise a loss inspired by a dimension reduction tool, multidimensional scaling [6]. By doing so, the feature extractor \( N \) can then also be trained in an adversarial manner to minimise the multidimensional scaling loss and to maximise the domain discrimination loss. Once trained, the features can finally be used for one-class classification.

3.2 The Multidimensional Scaling Loss

Denoting the input data as \( X \) and the features learned by the neural network as \( F \), we propose to define the multidimensional scaling loss as

\[
\mathcal{L}_F = \sum_{S \in \{ \text{Source, Target} \}} \frac{1}{|S|} \sum_{(i,j) \in S} \| X_i - X_j \|_2 - \hat{\eta}_S \| F_i - F_j \|_2^2,
\]

where

\[
\forall S \in \{ \text{Source, Target} \}, \quad \hat{\eta}_S = \text{Argmin}_{\tilde{\eta}_S} \mathcal{L}_F(\tilde{\eta}_S).
\]

From an optimisation perspective, the minimisation of this loss is equivalent to that where \( \eta_{\text{Source}} = 1 \) and \( \eta_{\text{Target}} = \hat{\eta}_{\text{Source}}/\hat{\eta}_{\text{Target}} \) such that we can define the loss as

\[
\mathcal{L}_F = \sum_{S \in \{ \text{Source, Target} \}} \frac{1}{|S|} \sum_{(i,j) \in S} \| X_i - X_j \|_2 - \eta_S \| F_i - F_j \|_2^2,
\]

where

\[
\eta_{\text{Source}} = 1, \quad \eta_{\text{Target}} = \text{Arg min}_{\tilde{\eta}_{\text{Target}}} \mathcal{L}_F(\tilde{\eta}_{\text{Target}}).
\]

Equation (4) has a closed-form solution that allows one to compute at each training step the optimal scaling parameter given the current features. Since the scaling parameter of the source dataset, \( \eta_{\text{Source}} \), is fixed to 1, and since source and target will be encouraged to overlap to maximise the domain discriminator loss, the values for \( \eta_{\text{Target}} \) are in fact quite constrained and did not lead to instabilities during training.

The minimisation of this loss encourages the latent space to conserve inter-sample relationships for both the source and target sets. The latent space is a non-linear transformation of the original space such that the between-sample distances are preserved as well as possible. Our proposed loss considers source and target independently, thus allowing for independent scaling and possibly mitigating distribution shifts due to translation, noise, rotations, and scales. The adversarial discriminator will also ensure that both source and target distributions overlap in the latent space.

4 Experiments and Results

4.1 Experimental Design

To demonstrate the effectiveness of the approach, we test the proposed architecture and loss on three open datasets. The experimental design is similar in the three cases. First, the anomaly detection is performed with Hierarchical Extreme Learning Machines (HELM) [20] on the target domain with a decreasing number of samples used for the training. The number of training samples is reduced either until it becomes too small to train a neural network, or until the balanced accuracy (BA) of the detection shows a clear drop. Second, this insufficient number of samples is used as the target training set and another dataset with different conditions is used as the source. These two datasets are then used to train, on the one side, the proposed architecture (ADAU) and, on the other side, another HELM as a baseline.

Architecture. Finding optimal network architectures for unsupervised tasks is an open research question, one not yet solved. Due to the impossibility of validating the model on the basis of its anomaly detection abilities—since
it is assumed that, at training time, no examples of faults are available—the traditional training/validation split or cross-validation cannot be performed. Thus we designed the networks based on our experience with HELM used as an anomaly detector. HELM consists in the stacking of a single-layer auto-encoder, with a single-layer one-class classifier ELM trained on the target value 1. In short, the auto-encoder devises features that are combined in the second layer into a single scalar, whose distance to the training target value is monitored. For each sample, this value is compared to a statistical descriptor of this distance computed with a healthy validation dataset. Here, this descriptor is 1.2 times the 99.5th percentile, as in [20]. The validation set is always set to a size of 25%, that of the training set size, mimicking an 80%/20% split. Empirically, the number of neurons used for HELM can be set according to the elbow approach [27].

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Figure 3: Anomaly Detection Transfer on CWRU (load 3 to 0). (a) All faults (b) Ball 14 mm Fault (lowest BA among all faults for HELM trained with 5% of the healthy set at load 0).

Table 1: CWRU - Balanced Accuracy (BA), False Positive rate (FP) and their standard deviation (Std) for the CWRU 0→3 experiment for different training size

| Target Only | 5% Target + Source |
|-------------|--------------------|
| HELM        | M A                |
| 50% 20% 10% 5% | + 5% +10% +20% | +5% +10% +20% |
| BA 99.77 98.88 99.08 97.39 | 97.87 98.57 | 98.83 99.80 |
| Std 0.93 2.89 1.86 8.42 | 4.42 3.53 | 1.66 1.33 |
| FP 0.00 0.00 0.67 0.22 | 2.33 1.00 | 1.67 1.33 |
| Std 0.00 0.00 0.54 0.27 | 2.49 1.47 | 2.22 2.40 |

Defect on Ball, 14 mm

| BA 97.25 92.85 94.32 91.94 | 93.60 95.60 | 97.08 99.08 |
| Std 2.28 1.93 2.70 8.06 | 4.76 3.81 | 1.42 1.14 |
| FP 0.00 0.00 0.67 0.22 | 2.33 1.00 | 1.67 1.33 |
| Std 0.00 0.00 0.54 0.27 | 2.49 1.47 | 2.22 2.40 |

M: HELM trained with Mixed dataset (Source + Target)
A: Results using ADAU

Performing the elbow method on HELM for these data, we find that HELM can be designed with 10 neurons in the auto-encoder and 50 neurons in the one-class classifier. ADAU is then constructed using these values. The results of this experiment are reported in Table 1 and illustrated in Figure 3, first for the aggregated balanced accuracy over the 15 available faults and second for the fault with lowest balanced accuracy when HELM is trained with 5% of the data, that is, the Ball defect of size 14 mm. From the results, one can see that the bearing dataset has very little variations within each load mode. 5% of the dataset is still enough to train a detection algorithm with over 97% balanced accuracy. Nevertheless, using data from the source always improves the results and this improvement is always higher for our method, ADAU, as compared to simply combining the data with HELM. Last, one can observe that adding more data from the source helps as long as both source and target data are in similar numbers (up to a factor 2). When too many source data are used, the performance on the target decreases.

4.3 Jet Engine Monitoring

In the previous experiment, it appeared that if the operating mode of the target domain is stable, ADAU can offer some improvements, but they are limited due to the high performance of the anomaly detector trained solely on the target, even when trained on a very low number of samples.
In this experiment, we propose to test the methodology on an adaptation task where source and target have five operating modes, including three transients, but only one is available for the target at training time. For this experiment, we use the Advanced Geared Turbofan 30,000 (AGTF30) [5] to simulate flight data for two different planes. We take as a simulation input two flight profiles (altitude, Mach number and power lever angle) downloaded from the flight tail NASA open source repository, tail 670 and tail 687. The flight profile altitudes are represented in Figure 4. The source unit is tail 687, simulated with the default parameters of the AGTF30 model. The target unit is tail 670, where the capacity and efficiency of the fan, and of the low-pressure and high-pressure turbines and compressors, have been reduced to 98%. For the target, we simulated six independent faults, each corresponding to a drop of 0.5% in capacity or efficiency of the fan, the high-pressure turbine, or the low-pressure turbine.

For each of the five operating modes, (1) take-off, (2) high-altitude cruising, (3) descent, (4) mid-altitude cruising, and (5) landing, as well as for each fault type, we extract 500 engine cycles, illustrated as the blue and red rectangles in Figure 4. For the target, however, only the data from the second operating mode, high-altitude cruising, in the healthy condition, are available at training time. This is illustrated with the red rectangle in Figure 4.

Based on these data, we use the elbow approach to estimate the number of neurons of the network and find 30 neurons for the HELM auto-encoder, and therefore for the feature extractor, and 100 neurons for the one-class classifier.

The results under each operating mode are presented in Table 2 and illustrated in Figure 5. As expected, HELM trained solely on samples from the second operating mode of the target detects all other operating modes as anomalous, which leads to 100% FPR and thus a BA of 50%. For these modes, adding data from the source can only help, but the improvement is limited by the distribution shift between the two planes. In these cases, performing the alignment significantly improves all results, with the BA reaching up to 100% as long as the number of samples added from the source remains within the same order of magnitude as the number of training samples from the target (up to a factor 2-3 as for the CWRU case study).

### 4.4 MNIST - MNIST-M as Anomaly Detection

Complex industrial systems often operate in an extremely stable manner as long as the operating conditions are not changed either due to a new operation (e.g., a flight transitioning from cruising to landing) or an environmental change (e.g., seasonality).

To test the proposed solution in a context with more diversity within the main class, and to show the generalisability of the solutions to other fields, we propose in this last experiment to perform the alignment on the MNIST to MNIST-M transfer task [9]. The MNIST dataset [12] contains 55 000 handwritten images of the 10 digits. The images are of size $28 \times 28 \times 3$. The MNIST-M dataset contains patches from the BSDS500 [3], clipped with MNIST digits, as illustrated in Figure 6.

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1[https://c3.nasa.gov/dashlink/projects/85/resources/?type=ds](https://c3.nasa.gov/dashlink/projects/85/resources/?type=ds)
Figure 5: Anomaly Detection Transfer on Engine simulated with AGTF30. Results for each operating mode averaged over all faults. When training with the target data of operating mode 2, most resulting models have 100% false positive rates on other modes.

Figure 5: Anomaly Detection Transfer on Engine simulated with AGTF30. Results for each operating mode averaged over all faults. When training with the target data of operating mode 2, most resulting models have 100% false positive rates on other modes.

Table 2: AGTF30 - Results (BA, FP, and their standard deviation Std) for the 5 operating modes using target data from mode 2.

| Target Only | 2% Target + Source |
|-------------|---------------------|
| HELM        | M +2% A | M +5% A | M +10% A |
|             | 10% 5% 2%   |       |        |
| Operating mode 1: Ascent |
| BA          | 53.75 50.67 50.05 | 85.78 99.30 | 83.29 100.00 |
| Std         | 3.12 0.90 0.10 17.44 0.61 0.00 | 19.56 0.52 0.00 | 21.91 8.91 |
| FP          | 92.49 98.65 99.90 | 10.55 1.40 0.52 | 0.52 1.15 0.00 | 5.17 1.47 |
| Std         | 6.24 1.79 0.21 16.25 1.23 0.00 | 0.64 1.03 0.00 | 3.58 2.29 |
| Operating mode 2: High-Altitude Cruising |
| BA          | 80.87 91.05 91.43 | 84.98 100.00 | 78.45 100.00 |
| Std         | 20.86 6.55 3.20 22.90 0.00 0.00 | 23.68 0.00 0.00 | 23.03 8.98 |
| FP          | 8.78 15.91 17.15 | 0.04 0.00 0.00 | 0.00 0.00 0.00 | 0.00 0.00 |
| Std         | 14.55 9.86 6.39 0.07 0.00 0.00 | 0.00 1.03 0.00 | 1.50 0.00 |
| Operating mode 3: Descent |
| BA          | 52.95 50.71 50.07 | 87.29 100.00 | 87.69 100.00 |
| Std         | 2.13 0.87 0.15 16.89 0.00 0.00 | 16.64 0.00 0.00 | 17.42 8.98 |
| FP          | 94.11 98.58 99.85 | 11.67 0.00 0.00 | 0.00 0.00 0.00 | 0.00 0.00 |
| Std         | 4.25 1.75 0.29 11.78 0.00 0.00 | 0.00 1.03 0.00 | 0.00 0.00 |
| Operating mode 4: Lower Cruising |
| BA          | 50.00 50.00 50.00 | 93.33 100.00 | 88.33 100.00 |
| Std         | 0.00 0.00 0.00 17.00 0.00 0.00 | 0.00 1.03 0.00 | 17.99 8.98 |
| FP          | 100.00 100.00 100.00 | 0.00 1.13 0.00 | 0.00 1.92 0.00 | 0.00 2.50 |
| Std         | 0.00 0.00 0.00 0.00 0.00 0.00 | 0.00 3.59 0.00 | 0.00 5.01 |
| Operating mode 5: Landing |
| BA          | 50.00 50.00 50.00 | 93.33 99.43 | 88.33 99.04 |
| Std         | 0.00 0.00 0.00 17.00 0.80 1.79 | 21.15 1.79 0.00 | 18.51 9.09 |
| FP          | 100.00 100.00 100.00 | 0.00 1.13 0.00 | 0.00 1.92 0.00 | 0.00 2.50 |
| Std         | 0.00 0.00 0.00 0.00 1.60 0.00 | 0.00 3.59 0.00 | 0.00 5.01 |

M: HELM trained with Mixed dataset (Source + Target)
A: Results using ADAU
Here we consider one digit as the main class (digit 0), and all others as anomalies. The dataset is made up of 5455 images of class 0 for source and target and 49545 anomalies. The proposed loss in Equation (1) necessitates a distance computation between samples. A relevant distance measure between images is still an open research question. In this work we choose to use the image Euclidean distance (IMED) \[17, 22\] for three reasons. First, it is similar to the traditional Euclidean distance used in the other case studies. Second, experiments have shown its robustness to scale, translation, rotation, image size, and noise \[22\]. Third, since its implementation requires only the pixel-wise Euclidean distance computation after the application of a Gaussian blur kernel to the image, it can be computed on the vectorised representation of the image. This allows us to use the same architecture as in other experiments. If \(N^2\) is the size of the images, the IMED distance is defined as:

\[
d_{IMED} = \sqrt{\sum_{i=1}^{N^2} \sum_{j=1}^{N^2} g_{ij} \cdot (x_i - y_i) \cdot (x_j - y_j)},
\]

where

\[
g_{ij} = \frac{1}{2\pi\sigma^2} \exp \left( -\frac{\text{dist}(P_i, P_j)^2}{2\sigma^2} \right)
\]

and where \(\text{dist}(P_i, P_j)\) denotes the Euclidean distance between the pixels \(i\) and \(j\).

Similar to other experiments, we infer the number of neurons in our architecture with the elbow approach on HELM. The HELM auto-encoder has 16 neurons and, therefore, the two layers of the feature extractor also have 16 neurons. The one-class classifier has 100 neurons.

The results are presented in Table 3 and illustrated in Figure 7. The results show that when the number of training examples from the target diminishes, the one-class classifier loses accuracy, mostly due to its incapacity to learn the main class properly, indicating some variability in the main class. In this case, mixing the data without alignment helps on average but with a high results variability, probably due to variability in the random selection of the source and target samples used for training. With the alignment, results improve significantly, reaching up to 90% BA.
Table 3: MNIST - Results (BA, FP, and their standard deviation Std) for the MNIST to MNIST-M transfer task.

| Target Only | 1% Target + Source |
|-------------|---------------------|
| HELM        | M A                 |
| 10%         | +1%                 |
| 5%          | +5%                 |
| 1%          | +10%                |

| BA  | 95.23 | 93.69 | 66.21 | 67.38 | 78.31 | 71.56 | 86.96 |
|----|-------|-------|-------|-------|-------|-------|-------|
| Std | 0.41  | 0.74  | 1.82  | 5.22  | 7.49  | 10.15 | 3.80  |
| FP  | 0.43  | 1.08  | 11.31 | 18.88 | 12.71 | 13.94 | 6.78  |
| Std | 0.33  | 0.59  | 8.13  | 6.45  | 6.83  | 6.46  | 5.94  |

M: HELM trained with Mixed dataset (Source + Target)
A: Results using ADAU

5 Conclusion

Throughout the three presented case studies, we demonstrated that the accuracy of data-driven anomaly detection methods depends on whether the training data covers the variability of the main class. When this is not the case, data from other related sources can be used in complement. Yet when the different data sources have a domain shift (e.g. a different engine setup, images of a different nature, or bearings with a different load), the anomaly detector can fail to recognise the main class. This can be mitigated by aligning the domains with an adversarial architecture and the proposed loss. This setup has two limits, however. First, the source and target domain should have a number of training samples in the same order of magnitude, probably due to the difficulty of training the domain discriminator in an unbalanced setup. This might limit the additional experience that can be introduced by the source. Second, this approach benefits the final results if the source offers additional unobserved operating conditions. In stable operation, similar to the CWRU experiments, results showed little difference between an AD trained on the few available target samples and an AD trained on both source and target. In the future, this work may be extended to multi-source alignment in an attempt to collect operating condition experience from whole fleets of units.

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