DANNTe: a case study of a turbo-machinery sensor virtualization under domain shift

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Abstract

We propose an adversarial learning method to tackle a Domain Adaptation time series regression task (DANNTe). The task concerns the virtualization of a physical sensor of a turbine with aim to build a reliable virtual sensor working on operating conditions not considered during the training phase. Our approach is directly inspired by the need to have a domain-invariant representation of the features to correct the covariate shift present in the data. The learner has access to both a labeled source data and unlabeled target data (Unsupervised DA) and is trained on both, exploiting the minmax game between a task regressor neural network and a domain classifier neural network. Both models share the same feature representation in terms of a feature extractor neural network. This work is based on the work of Ganin et al. [7]; we present an extension suitable to be applied to time series data. The results report a significant improvement in regression performance, compared to the base model trained on the source domain only.

1 Introduction

In recent modern applications, it is critical the ability to learn new concepts from a domain-dependent data and transfer them to related, but different contexts. Generally speaking, we refer to it as *transfer learning* [15]. In this context, the model is trained on a source domain or task and evaluated on a different but related target domain or task, where either the task or domains (or both) differ. A domain consists of a feature space and a marginal probability distribution. A task consists of a label space and an objective predictive function. Thus, a transfer learning problem [15] might be either transferring knowledge from a source domain to a different target domain or transferring knowledge from a source task to a different target task, or a combination of both. By this definition, a change in the domain may result from either a change in feature space or a change in the marginal probability distribution.

Unsupervised Domain Adaptation [17], with generalization bounds stated by Ganin et al. [3], [4] is a type of transfer learning where the task remains the same while the domains are different (transductive transfer learning). Formally, the learner has access to a labeled source dataset $S = \{(x_i^s, y_i^s)\}_{i=1}^{n_s}$ and an unlabeled target dataset $T = \{(x_i^t)\}_{i=1}^{n_t}$, where datapoints x^s and x^t are sample respectively from a source distribution P_s and a target distribution P_t both over X.

We seek to build a domain-invariant feature representation, where the emergent features are invariant with respect to the domain. We expect that a model based on domain-invariant features will perform with good performance in both domains, so that the difference between them is not very significant. Most of the literature focuses on problems applied to independent and identically distributed data; we

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try to fill this gap by addressing a problem concerning the time series where the time dependencies within the data are critical for a correct regression. In particular, we apply the unsupervised domain adaptation method to an industrial turbo-machinery context providing practical results and showing that domain adaptation can be an answer also applied to complex timeseries application, even in presence of a non-independently and identically distributed assumption.

1.1 Related works

The approach we follow attempts to match feature space distributions, however this is accomplished by modifying the feature representation itself. It is a related idea to Geneative Adversarial Netowrks (GAN) [8], [12], [18] while their goal is quite different (building generative deep networks that can synthesize samples).

Several line of research address the unsupervised domain adaptation task. The line of *Domain Invariant feature* aims to learn a domain-invariant feature representation, typically in the form of a feature extractor neural network. A representation is domain invariant if the features follow the same distribution regardless the input data are from source domain or target domain [9], [20], [16], [1]. The line of *Domain Mapping* aims to learn a mapping from one domain to another. The map is typically created at the pixel level [2], or trough a specific GAN [14] , where a generator performs adaptation translating a source input image to an image that closely resembles the target distribution. The line of *Normalization statistics* exploits the batch normalization layer [11] to learn domain knowledge [19]. The line of *Ensemble methods* consists of using multiple models [6] averaging their output to keep domains separated.

1.2 Use case

In turbo-machinery applications it is common to observe a domain shift. Domain shift can be generated from operative conditions not observed during test phase or from the environmental characteristics of the customer site, often different from those where the prototype is validated (test rig). In our specific case, a model of a physical sensor is learnt from prototype data and needs to be applied to fleet data, where that physical sensor is not present. In other words, our challenge is to combine the lack of the sensor in target data and the domain shift due to different features distribution. With this statement we are providing the needs to a unsupervised DA approach to deal with the observed domain shift.

1.3 DataSet

To validate our implementation (called DANNTe) we tested on prototype data, splitting source/target between winter and summer period respectively. In particular, the source domain is represented by timeseries collected during a winter period and the target domain acquired during a summer period. Dataset has been acquired from 30 sensors installed on a turbine running for test from December 2019 to August 2020. Winter data from December to February is used as labeled source dataset, and the summer data from June to July as unlabeled target dataset. Both the datasets are collected from the same machine in a prototype state where the conditional operation might be different and the environmental conditions generate two different distributions. We would like to remind that the fully supervised approach is not feasible in our real use case since no ground truth for y_t is available in target domain. The availability of the ground truth for the physical sensor in the target domain allows us to score the model performance at test-time.

2 The implemented library

2.1 Model

We adapted the Domain-Adversarial Neural Networks (DANN) by Ganin et al. [7] to a regression task (**D**omain-**A**dversarial **N**eural **N**etworks applied to **T**imeseri**e**s, DANNTe). It seeks to learn features that combine discriminativeness and domain-invariance. This is achieved by jointly optimizing the underlying features as well as two classifiers operating on these features: *label predictor* predicts class labels and the *domain classifier* discriminates between the source and the target domains. While the parameters of the label predictor are optimized in order to minimize their error on the training set,

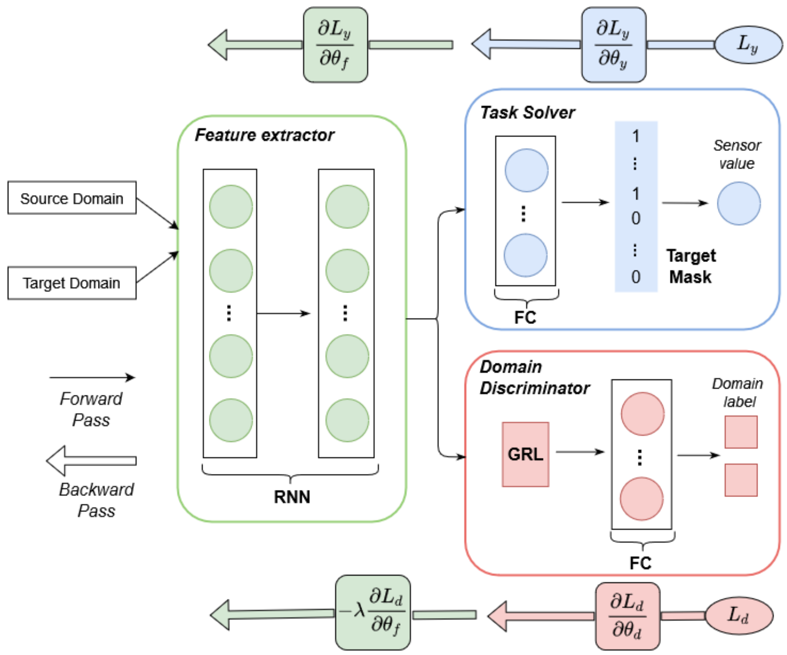

Figure 1: Architecture of our proposed approach (DANNTe), based on Ganin et al. [7]. Feature extractor weights are modified by both the task solver (in our case, a regressor trying to minimize the reconstruction loss) and the domain classifier (trying to minimize the source vs target domain classification loss). The gradient reversal layer acts so that a minimization problem is solved (instead of a min-max one), just reversing the sign of the domain classifier gradient during backpropagation.
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the parameters of the underlying deep feature mapping are optimized in order to minimize the loss of the label predictor and to maximize the loss of the domain classifier. The latter update thus works adversarially with respect to the label predictor encouraging domain-invariant features to emerge in the course of the optimization.

The architecture is composed by a feature extractor recurrent network stacked on two networks (see Fig. 1). The first head is a task solver (previously "label predictor") neural network, a regressor whose goal is to minimize the reconstruction loss for the source domain, where y is available. Its loss is not affected by target domain examples, which are skipped because of the target mask layer. The second head is a domain classifier neural network, aiming at discriminate examples coming from source from those coming from target domain, exploiting the x information, the only available in both domains. To correctly discriminate, a new dataset $U = \{(x_i, 0)\}_{i=1}^{n_s} \cup \{(x_i, 1)\}_{i=1}^{n_t}$ is built, where samples from source domain are labelled with 0 and samples from target domain are labelled with 1.

The task predictor loss L_y is the MSE, while the domain classifier loss L_d is the Negative Log Loss defined as:

$$L_d = -\frac{1}{n}\sum_{i=1}^{n}(y_i log(p(y_i)) + (1 - y_i) log(1 - p(y_i))) \tag{1}$$

where y_i denotes the binary variable (domain label) for the i-th sample, which indicates whether it comes from the source distribution (y_i = 0) or from the target distribution (y_i = 1).

The total loss combines the contribution of the losses of the two branches, defined as:

$$L_{tot} = L_y - \lambda L_d \tag{2}$$

where λ is the domain loss multiplier; λ influences the contribution of the domain classifier loss during backpropagation. Once trained, only the feature extraction and task solver parts are kept and used for inference.

2.2 Model adaptation

Our architecture (DANNTe) differs in some implementation details from the DANN vanilla architecture [7]. The differences in our implementation are due to the nature of our data (time series) and by some implementation choices made to optimize training time and have an end-to-end architecture.

Ganin et al. ([7]) propose to use the data in different formats according to the branch: the *task solver* expects the training data $\{(x_i^s, y_i^s)\}_{i=1}^{n_s}$, and the *domain classifier* expects the training data $\{(x_i^s, 0)\}_{i=1}^{n_s} \cup \{(x_i^t, 1)\}_{i=1}^{n_t}$. Using two different datasets to train the model causes the need to perform multiple forward and backward passes, making training computationally demanding. To reduce the computational complexity, we propose a solution based on the addition of a target mask layer.

The **target mask** layer modifies the loss L_y contribution of the *task predictor* for the samples belonging to the target domain, by assigning them a loss weight of 0. This approach is equivalent to computing the loss L_y first using only transformed samples from the source domain, and then computing the loss L_d using the combined batches. However, with this mask we significantly cut down training time, allowing to compute weight update in a single forward and backward pass.

Another proposal by Ganin et al. ([7]) is to build the datasets by i.i.d from P_s and P_t. In our specific use case, since we use an RNN (LSTM) as a *feature extractor*, generating the datasets by uniformly and identically distributed sampling would lose the temporal dependencies within the data and we cannot apply.

The solution we propose is to train the model by creating **equally divided batches** where half of each batch is filled with samples from the source domain, and half with samples from the target domain, keeping the temporal order. The reason why we select this approach is to hold the sequential behaviour of measurements in successive time slots, granted by having portion of batch with consecutive measurements.

3 Results

3.1 Performance assessment strategy

Model performance has been evaluated by exploiting the variable y which in this simplified use case is available in both domains. We remind once again that this ground truth will not be available in our real use case, instead.

The DANNTe regression performance has been compared to:

- an upper-bound performance, given by the case when ground truth is available also in target set, so that both source and target sets are used for a fully supervised training (*fully-supervised model*);
- a lower-bound performance, given by the case when we simply perform supervised training on source target data and directly apply the model to target domain data (*baseline model*).

3.2 Evaluation framework

Our evaluation framework considers two steps: model selection and model assessment. Model selection estimates the performance of different learning models, that includes searching the best hyper-parameters of the model, in order to choose the best one (to generalize). Model assessment evaluates the final model by its prediction error on new test data.

To correctly select the hyperparameters of our models, we use an outer and an inner grid-search. The outer grid-search is used to produce the first configurations of the hyperparameters where values from a very broad range are tested, for each hyperparameter. This allows us to have a first rough selection of values. Subsequently, the range of values to be used in the inner grid-search is selected starting from the results obtained in the outer grid search. Here values from a smaller range are tested, for each hyperparameter, for a finer tuning. To test each configuration produced by the outer or inner grid search we apply the k-fold cross validation with 4 folds and a validation percentage of 20%.

3.3 Model performance and comparison

Performance comparison summarized in Tab. 1 shows the improvement achieved using DANNTe, with respect to the baseline model. Related uncertainties are referring to the variance achieved trough cross validation phase.

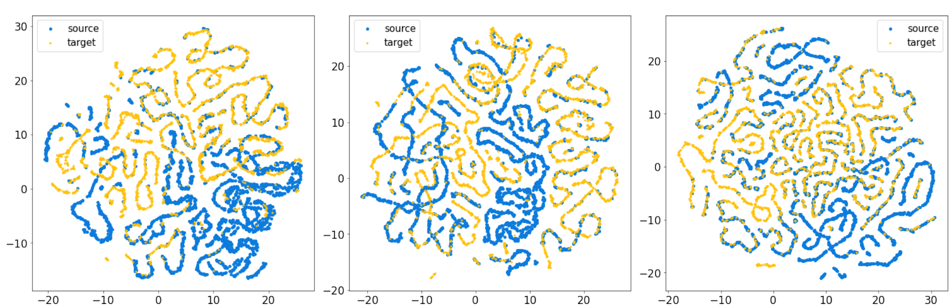
	MSE Source	MSE Target
Baseline model	**8.4** ± 0.1	3567.6 ± 0.9
DANNTe model	120.6 ± 0.2	**1398.2** ± 0.2
Fully-supervised model	16.4 ± 0.7	17.8 ± 0.8

Table 1: DANNTe performance compared to baseline and fully-supervised models. Metric MSE refers to the Mean Squared Error.

We found that the hyperparameter λ, which is the constant multiplier of the domain classifier's loss during backpropagation, plays a key role in feature extraction. The higher its value, the higher the influence of the domain classifier loss, meaning a stronger push towards domain invariance in the feature extractor. The network will therefore tend to find features that are shared by the two domains, but which are not necessarily good for regression task. A small λ, on the other hand, will cause the extracted features to be less domain-invariant but more effective to predict the signal in the source domain samples. For our experiments, we found that a value equal to 1, yielded the best performance.

3.4 Features encoding

To get a graphic insight about how the feature embedding changes with DANNTe, we use the UMAP method [13] to lower the embedding dimension to 2 (see Figure 2). From the comparison of Figure 2a corresponding to the baseline model and Figure 2b corresponding to the fully supervised model, we observe a clear clustering between source and target datasets. However, when we use the proposed approach, the representation in Figure 2c shows a lower ability to distinguish between clusters.



(a) Baseline model (b) Fully supervised model (c) Proposed approach

Figure 2: Data representation reduced to 2 dimensions using UMAP. We can observe a clear separation between the two domains (blue and yellow, summer and winter) using by the baseline model (a). Our DANN adaptation to timeseries (DANNTe) seems to construct a less discriminative feature representation.

3.4.1 Parameters

The configuration of the hyperparameters for the proposed baseline and the fully supervised models that yielded the best results (with ratings shown in Table 1) are the same: a LSTM with 2 layers (each with 64 neurons) and on top other 2 fully connected layers with 64 neurons. The activation function for the LSTM is the "tanh" and for the fully connected the "ReLU". The penalty applied was an elastic net regularization with value of 1.0e-5 for both L1 and L2. The best window size was 1.

The configuration of the hyperparameters for the proposed DANNTe that yielded the best results (with ratings shown in Table 1) are the following: a LSTM with 2 layers for the *feature extractor* (each with 16 neurons), a NN with one 8-neuron dense layer for the *task predictor* and a NN with one 32-neuron layer for the *domain classifier*. The activation function of the *task predictor* and the *domain classifier* is the "ReLU". The penalty applied was an elastic net regularization with value of 1.0^{-5} for both L1 and L2. The best window size was 1 with the batch size supplied to the model being 1024.

4 Conclusions

The results are promising and allowed us to improve the reliability of a model in two different domains, correcting the domain shift present in the data, showing how improvement is guaranteed if virtualization is based on features that combine discriminativeness and domain invariance. We adapted DANN method to a regression task applied to a industrial use case. Results report that the DANNTe approach improves performance. Despite there is still room for improvement in order to achieve results as close as possible to the fully-supervised approach, our findings show that is a promising approach also in real applications.

4.1 Future work

In the next future we will focus on an improved version of the feature extractor, evaluating a deeper autoencoder [10, 5] approach. Our work demonstrates how the loss of the discriminator is correlated with the ability of the network to do a correct regression in target domain, but we need to investigate further in how non-i.i.d. data could hamper the statement of the impossibility theorem [4].

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