Master Thesis – Task Description

Bridging the Domain Gap: Visualization Support for Transfer Learning on Time Series Data

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Motivation

End-of-line testing is an essential step in the production process to validate the functionality of units near the end of the production line [1]. Defective products or those not matching manufacturing tolerances must be rejected before the products are shipped. To shorten production cycles, automatic testing increasingly replaces manual inspection performed by human operators. A unit under test is exposed to a stimulus and its response is recorded by different sensors. The resulting multivariate time signals are analyzed for defect identification and classification.

For automatic defect classification, a data-driven model is needed. While real-world data from units functioning as intended might be plenty, data from units at or near failure is much sparser. In such cases, synthetic data can be used for training the model. In this way, training data can be generated in a controlled way, are available in large amounts, properly labelled and most often do not require prior data cleansing. However, a simulation model will not perfectly reproduce the real-world behaviour of a unit. Thus, the simulation domain and the real-world domain are related but not identical. Many statistical learning models, however, rely on the assumption that the training data and the samples to be classified are drawn from the same distribution. Applying a model trained on simulations directly to real-world measurements is therefore likely to result in a significant performance drop.

The assumption can be avoided by choosing a transfer learning approach, which aims at learning from a source domain a well-performing model on a related target domain [2]. Characterizing the domain shift, i.e. the relationship between the simulation data (source domain) and the real-world data (target domain) is essential to solve this task. Humans are usually good at transferring knowledge from prior experience when learning a new task, i.e. an experienced car driver can learn to operate a boat with less effort than someone who has never operated any vehicle. A human-in-the-loop approach involving interactive visualization therefore seems beneficial for transfer learning. As soon as the modeling pipeline is set up, the transfer learning can be applied as an automated process.

1. Set up defect classification model based on simulations
2. Adapt the classification model to real-world measurements

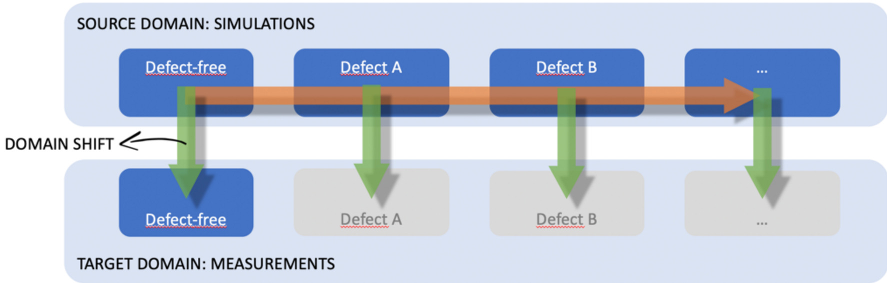

Figure 1 *The transfer learning problem: labeled samples of defective motors are only available in the source domain. Still, the domain shift can be characterized using data representing defect-free motors that are available in both domains. To classify unlabeled samples from the target domain, the model learned on the source domain needs to be adapted to the target domain based on the characterized domain shift.*

Problem Description and Approach

The goal is to bridge the domain gap between simulated and measured unit responses, such that a classification algorithm learned on simulation data can be applied to new (unlabeled) real-world data from sensor measurements. The units under test are electric motors, whose current dt. Strom signals are to be used for a defect classification. The transfer learning problem is characterized by a shift in the input domain (i.e. simulated vs. measured signals of the same motor) while the analysis task remains the same (i.e. classify the defect). The data are multivariate time series that are simulated/measured across various operating conditions. For defect-free motors, both simulated and corresponding measured signals are available. For defective motors, however, only simulated time series with corresponding defect labels are available. The lack of real-world training data for defective motors raises the need to learn from the simulated data a well-performing classifier that can be applied to real-word measurements (**Figure *1***).

We will focus on one-step transfer learning[1], which will likely be unsupervised[2]. The idea is to identify the relationship between source and target domain in order to align both domains by creating a domain-invariant feature representation [3]. If a classifier trained on the source domain performs well using the domain-invariant features, it is assumed to generalize to the target domain. Domain-specific features as well as statistics-based transfer functions have already been investigated in prior student work [4,5]. This master thesis is in particular motivated by the question how visualization can help exploit the human abilities for characterizing the domain shift between the simulated training data and the real-world target data to inform the creation of a shared feature space.

In a first step, the student will establish a characterization of the transfer learning task to be solved in order to inform decisions about applicable approaches. This will include reviewing whether creating a domain-invariant feature space seems feasible and beneficial for the use case present. This investigation will most likely result in an understanding of where in the process interactive visualization might be beneficial to steer the identification of domain-invariant features. Visual representations can then be developed to help the feature exploration by synchronising the time series of both domains, aiming at a fundamental understanding of their relationship, i.e. the domain shift. In this way, the

[1] See https://towardsdatascience.com/deep-domain-adaptation-in-computer-vision-8da398d3167f
[2] The availability of any labeled real-world samples needs to be clarified with the data provider.

feature identification will also benefit from domain experts being able to exploit a-priori knowledge of the unit under test and to apply scenario-dependent semantics and expectations. The proposed approach might be inspired by, but is not limited to, techniques related to time series analysis, side-by-side visualization, similarity search, anomaly detection or clustering to name just a few.

Expected outcome

The implementations and written master thesis should cover the following aspects:

- A characterization dt. Einordnung of the transfer learning task to be solved
- A review of prior works in scientific literature that frame and inspire the development of the proposed approach
- A visual-interactive strategy for identifying domain-invariant features that eliminate the shortcomings of directly applying a simulation-based model to the target domain
- A web-based prototype of the developed transfer learning strategy
- An evaluation of the proposed transfer learning strategy

Challenges

There are two main challenges for this thesis. First, there exists a large spectrum of approaches to transfer learning. The problem statement requires a careful selection of a suitable transfer learning technique under consideration of human-in-the loop aspects[3]. Second, it requires the development of appropriate interactive visualization techniques to realize a human-centered approach that allows engineers to bring in their domain knowledge in order to bridge the domain gap. This is not an easy task, as transfer learning is mainly studied in computer vision [6,7] and natural language processing where the main idea is to learn domain-invariant representations in deep neural networks. In contrast, few to no works that study interactive visualization for transfer learning exist to this date [8,9,10].

Scientific environment

As the described research is highly application-driven, it is important to consider the tasks and needs of operators in the targeted application domain. The use case and data underlying this master thesis description are provided by a research company in the field of mechatronics, whose engineers serve as domain experts. This master thesis is supervised by two researchers at IGD to provide adequate scientific support in the two disciplines “visualization” and “transfer learning” that join forces in this topic. Although both of us have a fundamental understanding of either discipline, Igor Cherepanov will be the main contact person for the “transfer learning” part, while Lena Cibulski will be the main contact person for the “visualization” part and the “digital manufacturing” context.

[3] The existing classification approach might also be considered.

Literature

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