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Program

Session 1. Chair: Thomas Vetterlein

9:00 W. Zellinger:
Moment Distances for Comparing High-Entropy Distributions
with Application in Domain Adaptation

9:30 M. Zwick:
Transfer Learning with Scenario-Invariant Time Series Analysis (ScITSA)
for Cyclical Processes in Manufacturing

Session 2. Chair: Bernhard Moser

10:15 A-M. Meder:
Optimization of Electrical Drives Using Deep Learning Techniques

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Deep Learning Based Trajectory Prediction and Anomaly Detection in Crowd

Moment distances for comparing high-entropy distributions with application in domain adaptation*

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Abstract

The L^1-convergence towards a small value of sequences of densities with high differential entropy is analyzed in terms of the ℓ^2-convergence of finitely many corresponding sample moments. Under appropriate regularity conditions, the density convergence is linear in the ℓ^2-norm of the difference between the moments with a bias term converging to zero at rate $O_p(n^{-1/2})$ for sample size $n \to \infty$. The analysis leads to a new target error bound for discriminative learning models applied on unlabeled test data with sample moments different from the training data. For this problem of domain adaptation, some ideas are proposed for moment based domain adaptation of neural networks. First numerical implementations are discussed and resulting open questions are stated.

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Transfer Learning with Scenario-Invariant Time Series Analysis (ScITSA) for Cyclical Processes in Manufacturing

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***Abstract*—This paper describes a transfer learning method for modeling sensor time series data. The method aims at removing the scenario specific information before the modeling of the individual time series data takes place. Domain knowledge is incorporated to find factors for the modeling of scenario differences. The learned correction formula generalizes to new scenarios without the need of collecting any new input data. On a real world case study on metal bending, generalization would not be possible without the proposed method. On already seen scenarios the prediction error is significantly reduced by around 10%-30%, when compared to the standard approach of modeling each scenario independently.**

I. Introduction

In intelligent manufacturing, machine learning is commonly applied in various application domains, including control, optimization, fault detection and smart maintenance. The success of such applications depends on the quality of the involved machine learning models, which in turn not only heavily depend on data quality but also on the sheer amount of available data. Modern machine manufactures are well aware of the potential of data-driven applications and collect increased amounts of data into manufacturing databases. However, a frequently recurring problem in intelligent manufacturing is that the collected data is too heterogeneous to simply model it with standard machine learning approaches. In particular, from the cyclical manufacturing processes data is collected from different operating conditions and environments – called scenarios. For example, in practical applications, the different data distributions of the individual scenarios may be caused by differences in machines, machine settings, tools or workpiece materials. Standard machine learning techniques rely on the assumption that the entire data, both for training and for testing, underlies the same data generation process. However, this assumption is often violated when data is collected from different scenarios. Thus, using standard machine learning approaches requires to model each scenario independently, which, however, would require expensive and time consuming data collection efforts.

To remedy the described heterogeneities in data distributions, methods from the relatively new methodologies of transfer learning [2] and multi-task learning [3] can be used to best facilitate all information contained in the different scenarios. Multi-task learning leverages useful information from multiple related scenarios to help improve the generalization performance of all scenarios [3]. Transfer learning methods extract knowledge contained in related source scenarios (with large amounts of data) and transfer it to target scenarios (with only little or no available data) [2]. This paper addresses the transfer learning subtask of domain generalization [4], where, provided data from a representative set of training scenarios no data at all is required for the generalization to previously unknown scenarios.

This paper focuses on transfer learning problems from cyclical process problems in manufacturing, where predictions are based on time series data (i.e., data that is collected over time) collected from individual production steps. In industrial manufacturing cyclical processes are frequently recorded during the processing of individual workpieces. For example, a pressure or force curve is recorded for the duration of mounting or deforming of a each single work piece, which in turn can be used for tasks such as the reduction of work piece tolerance or product quality monitoring. In such problems, the data is most commonly collected from workpieces with different machine, machine configurations, tool settings or materials. The proposed *Scenario-Invariant Time Series Analysis (ScITSA)* method can be used to maximality leverage the available information by facilitating the joint modeling of such heterogeneous scenario data. In particular, ScITSA aims at removing the mean differences of scenarios and enables the joint modeling of different tool and machine settings by subsequent machine learning models. The model is *solely* based on parameters that describe process knowledge about the scenarios that do not change during the process (e.g tool, machine, workpiece configurations) and can be applied to new Scenarios, e.g. a different set of tools, without the need of collecting any additional training data. The proposed

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method is based on the idea of the parameter-based multi-task learning approach presented in [3], where coefficients of neighboring models are either shared or forced to be similar. Our proposed method differs to their presented approach by facilitating process knowledge and by applying it to different points in the time series – where stronger similarities are enforced between contiguous time steps. The corrected data from the different scenarios is more homogeneous and easier to learn by subsequent machine learning tasks. Furthermore, the learned correction formulas generalize to unseen scenarios. To our best knowledge no comparable methods exists that was specifically designed for cyclical time series data or any other kind of time series data in general. Based on an real world problem in intelligent manufacturing we show that prediction accuracy (which in our application corresponds to variations in the individual work peace) can be significantly improved by removing shifts in the time series distribution with SciTSA.

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Optimization of Electrical Drives Using Deep Learning Techniques

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Abstract – In order to be effective in electrical drive-design use cases, multi-objective optimization algorithms must rely heavily on model-based surrogate evaluators (i.e., regression models) that replace the finite element simulations. Surrogates based on various machine learning paradigms (like shallow multi-layer perceptrons, support vector machines, radial basis functions) have been previously tested with mixed success. As recent types of deep structured neural networks have shown very promising results in several application fields, the goal is to test the potential of these advanced machine learning techniques in the context of existing electrical drive design frameworks.

Deep Learning Based Trajectory Prediction and Anomaly Detection in Crowd

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Abstract

Understanding behavior patterns in dynamic environments is one of the approaches towards procuring safety not only in for autonomous driving but for such areas as intelligent surveillance, smart sports systems, etc. In this work, we investigate state-of-the-art approaches for prediction of human trajectories in different environments. We will provide analysis of the method's benefits and drawbacks. In addition, We will provide further investigation towards anomaly detection approaches.