Abstract

Multivariate time series classification has been broadly applied in diverse domains over the past few decades. However, before applying the classification algorithms, the vast majority of current studies extract hand-engineered features that are assumed to detect local patterns in the time series. Therefore, the efficiency and precision of these classification approaches are heavily dependent on the quality of variables defined by domain experts. Recent improvements in the deep learning domain offer opportunities to avoid such an intensive hand-crafted feature engineering which is particularly important for managing the processes based on time-series data obtained from various sensor networks. In our paper, we propose a framework to extract the features in an unsupervised (or self-supervised) manner using deep learning, particularly stacked LSTM Autoencoder Networks. The compressed representation of the time-series data obtained from LSTM Autoencoders are then provided to Deep Feedforward Neural Networks for classification. We apply the proposed framework on sensor time series data from the process industry to detect the quality of the semi-finished products and accordingly predict the next production process step. To validate the efficiency of the proposed approach, we used real-world data from the steel industry.

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1. Introduction

It is a crucial requirement for manufacturing enterprises to be able to react on certain situations in the market or in the internal production environment in real-time. There is a strong need to leverage the latest big data technologies, novel machine learning and artificial intelligence methods for monitoring, predicting, and thereby improving the manufacturing processes. For this purpose it is necessary to operationalize big data driven predictive analytics by embedding it to the business, operation and manufacturing processes which supports human experts in making critical business decisions by providing actionable insights or acting as a fully automated decision making system [1]. The enterprises can create value only by making the predictive analytics as an integral part of the business processes and operational decisions [2].

The main purpose of process monitoring in the manufacturing environment is identification of abnormalities and faults in process operations. Industrial process monitoring tasks are mainly categorized as (i) fault detection, (ii) fault identification and diagnosis, (iii) estimation of fault magnitudes, and (iv) product quality monitoring and control [3]. The techniques for monitoring the operational processes that rely on diverse analytical methods are classified into three groups: (i) quantitative model based methods, (ii) qualitative model based methods and (iii) process history based or data driven methods [4]. Model based approaches are based on first-principle methods and rely on the concept of residual analysis. They compute the residuals by comparing the estimated values with those of the a-priori known model and detect the anomalies. Although the model based methods are the most reliable approaches for process monitoring, such techniques suffer several disadvantages, as in the majority of cases the analytical description of newly developed complex industrial processes are unavailable and it is a time-consuming issue for domain experts to obtain it.

On the contrary, process history based data-driven approaches don’t require a pre-determined model since the models are obtained from a large amount of available historical process data. As one of the most important data-driven modelling approaches for diverse industrial process monitoring tasks, time series classification has found a broad range of applications in both discrete and process industries. However, current solutions to (multivariate) time series classification problems in the complicated process industry settings appear to be unsatisfactory since they heavily rely on domain experts for extracting the hand-crafted features. The requirements for real-time and immediate processing of stream data from Internet of Things (IoT) networks, and the concept drift which is referred as the evolution of behavior patterns in the sensor data over time, mitigate the effectiveness of conventional feature engineering and machine learning methods. Furthermore, the non-stationary, non-linear and dynamically evolving nature of the sensor data, which serve as valuable input for process monitoring modelling and the necessity to capture temporal relationship in the time series data, demand a novel design of machine learning algorithms. These approaches should satisfy the computational efficiency with a desired level of prediction accuracy and precision.

The present paper aims to propose a multi-stage deep learning to address these challenges in the multivariate time series classification problem for monitoring the product quality in the process industry. The contribution of the present paper is twofold: (i) the application of deep learning technique, particularly the stacked Long-Short Term Memory (LSTM) Autoencoders, to build hierarchical representations from unlabelled multivariate sensor time series data and (ii) the application of deep feedforward neural networks to make the cost-sensitive classifications by incorporating the knowledge by domain experts about the financial consequences of the prediction results. We evaluate the proposed approach in a real-world use case from the steel industry. As a process industry, the steel industry has quite special characteristics when evaluating data spanning the whole steel production process. In our case we attempt to predict the post-processing activities for semi-finished steel products depending on the steel surface quality. For this purpose we consider the sensor data which track various parameters of the steel continuous casting plant throughout the steel casting process and chemical data which describe the chemical compounds added to a steel casting mix based on the product qualities that are planned for an upcoming steel batch.

The remainder of the paper is organized as follows: Section 2 introduces a brief review of the related works for time series classification problems. Section 3 provides an overview to the proposed multi-stage deep learning approach and discusses the LSTM Autoencoder stage for feature extraction and deep feedforward neural networks for classification problem. Section 4 introduces the case study. Section 5 introduces the experiment settings, evaluation metrics and empirical results. Section 6 concludes the paper and discusses the future work.
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