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Analysis of Neural Network Training Algorithms for Implementation of the Prescriptive Maintenance Strategy

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Abstract. This paper presents a proposal to combine supervised and semi-supervised training strategies to obtain a neural network for use in the prescriptive maintenance approach. It is required in this approach because of only partially labelled data for use in supervised learning, and additionally, this data is predicted to expand quickly. The main issue is the decision on which are suitable training methodologies for supervised learning, having in mind using this data and methods for semi-supervised learning. The proposed methods of training neural networks with supervised and semi-supervised training to receive the best results will be tested and compared in further work.

Introduction

One of the trends in modern applications of artificial intelligence methods is increasing productivity by implementing the prescriptive maintenance approach. This allows to speed up the response in a failure or downtime. In particular, the system can diagnose the system condition online, predict possible problems that may occur in the future, and inform the operator using a system of recommendations and warnings. Moreover, this approach is in line with the Industry 4.0 strategy. There are many approaches to building a prescriptive maintenance system [1] in the literature, including artificial neural networks with machine learning and data mining algorithms.

The practical use of artificial neural networks requires the design of the structure and the training process that can be performed using the machine learning method. Machine learning is characterised by high data processing and real-time computing potential, making it suitable for compensating for the shortcomings of traditional risk analysis methods in infrastructure maintenance management. He et al. developed a generative adversarial network (GAN)-based semi-supervised learning method to construct real-time risk-based early warning systems [2]. Fuzzy logic rules estimated the risk quantitatively, while a convolutional neural network (CNN) g warning models. Risk analysis can efficiently classify a dataset obtained from equipment or processes. However, contemporary publications indicate a high degree of complexity of this process, making it impossible to determine the risk for all possible situations. Therefore, the results of supervised training are insufficient and sometimes even impossible. At the same time, self-taught learning may be widely applicable to solve various practical classification problems, which was postulated by Raina et al. in [3].

Semi-supervised training combines conventional methods using standard samples, each containing a vector of inputs and a corresponding vector of expected outputs, with fully unsupervised training methods. In the second case, training samples only include an input model, and the whole process is self-organised. Thus, the network's responses are arranged through the spontaneous formation of local interactions between neurons. Some general principles of building

an artificial network structure, data preparation and in-depth training using both approaches were presented by Goodfellow et al. in [4]. The research currently being carried out on semi-supervised artificial neural network training methods, algorithms, and practical applications cover many aspects, including:

- conducting the selection and classification processes on the available data to extract sample sets for combining the supervised and unsupervised training process. Data analysis is an indispensable part of the research process, especially when previous test results are unavailable. This is indicated, among others, by publications by Englund et al. [5] concerning meta-analyses of data selection criteria for stream predation experiments and by Hatush et al. [6], where the authors evaluate contractor prequalification data through the formulation of selection criteria and success factors;
- analysis of the available mechanisms and algorithms of semi-supervised training to solve the research problem posed, such as node label learning from unbalanced data [7]. The Hebb association rule, Kohonen's rule, and hybrid methods can be distinguished among the functional self-organisation algorithms. Bedekar et al. [8] used the Hebb rule to build a fault detection mechanism in power systems. B.S. Yang et al. [9] utilised the Kohonen network to diagnose faults of rotating machinery. In contrast, F.A. Souza et al. [10] used a Kohonen network with cascade perceptron to locate flaws in rural distribution feeders. Similarly, Z. Chen et al. [11] built a hybrid deep computation model for aeroplane engine fault detection. Verification of the results obtained using various types of self-organisation by comparing them with those generated by the neural network trained only in the fully supervised process indicates [8, 10] that the semi-supervised approach may positively affect the effectiveness of detecting emergencies;
- conducting the process of regularising the neural network to extend the possibility of generating correct answers for training patterns and new data. This kind of research was carried out by, e.g. Pretorius et al. concerning noise regularised deep neural networks [12] and Didcock et al. for neural network model averaging [13];
- analysis of the necessity and frequency of potential relearning the neural network model based on the obtained results of the preliminary training. An example of neural network dynamic relearning was provided by Li et al. [14]. This allows to acquire new knowledge on the requirements for the necessity and effects of cyclical re-training of neural networks in the context of the conditions changing with time during the operation of these networks;
- the issue of the performance of systems based on neural networks, including the impact of their speed on the confidence level of the generated results. Hence, sometimes there is a need to perform additional tests to determine the balance between the rate of action and the level of confidence in assessing the risk of emergencies. W. Jiang et al. dealt with optimising neural network operation for real-time multitasking applications [15].

This work will develop general guidelines for the neural network model training using different methodologies with full and partial supervision for the Prescriptive Maintenance strategy (RxM). It is advantageous when the created RxM system lacks the full expert knowledge necessary to determine the risk of all possible exceptions and emergencies. In particular, the results of analyses of the use of static and dynamic data samples and the possibility of independent adaptation of the neural network to the new realities of work (new devices, previously unknown types of failures), while maintaining an appropriate balance between speed and efficiency, may be helpful.

The issues discussed in this article may be of interest to a wide audience using data-driven data analysis methods, including in materials sciences [16-19], machining [20-22], construction of

internal combustion engines [23], energy control [24, 25], mechanics of solids [27, 28], civil engineering [29, 30], and even in military equipment development [31, 32]. The provided analysis may be used in analogous situations requiring the creation of appropriate predictive approximators [33-35] and classifiers [36, 37].

Neural Network Training Approaches

The combination of the supervised and semi-supervised training strategies to obtain a neural network for use in the prescriptive maintenance approach can solve the problem of a big amount of data, which is only partially labelled, requires knowledge of experts, and will be continually expanded in time.

A proposition is to first use adequate training algorithms for supervised learning but with the possibility of based on its methods for semi-supervised learning. A combination of labelled and unlabelled data will be used for semi-supervised learning. Testing and comparing different training strategies for supervised learning will narrow the possible options for training methods for unsupervised learning.

The proposed strategy for neural network training algorithms to implement the prescriptive maintenance is shown in Fig. 1. The first stage describes preparing labelled data and experimenting with different types and methods of training neural networks using supervised learning. In the second stage, results and conclusions of the first stage with the unlabelled data are used to select proper training methods for semi-supervised learning.

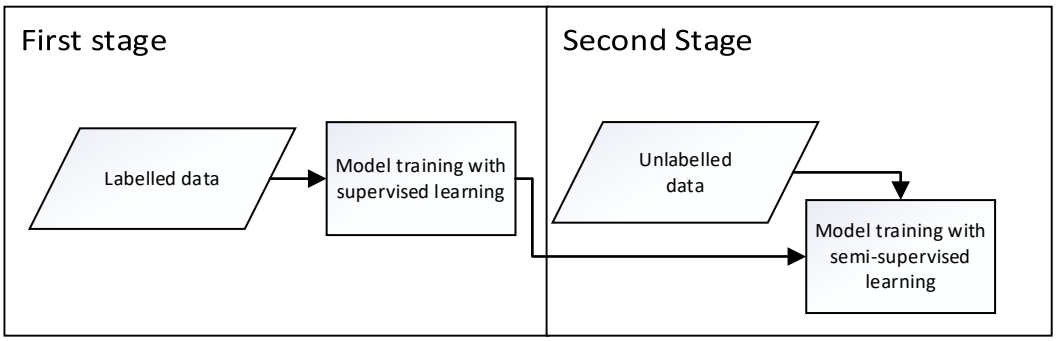

Fig. 1. Process of using supervised and semi-supervised learning for prescriptive maintenance

Supervised learning. There are two main types of learning problems. A classification involves predicting a class label, and Regression involves predicting a numerical label. The problem with Prescriptive Maintenance is that it can apply to both because maintaining the infrastructure in the enterprise in such a way that it retained all the desired functionalities and reflected the strategies and their compilations as faithfully as possible, at the same time omitting issues that are irrelevant to the strategy can be categorised in different ways. For input data (labelled and not), characteristics for maintenance processes such as device architecture (components of the device, device topology), age of devices, frequency of failure, frequency of maintenance, conditions in which they operate devices, measurement data from these devices, etc. are used. Another problem to be solved will be the development of metrics, which are connected with maintenance strategies, e.g. RBM (Risk Based Maintenance), CBM (Condition Based Maintenance) or TBM (Time Based Maintenance).

Multi-Task learning focuses on fitting a model one dataset for multiple related problems, and it improves when working on numerous tasks instead of one. It can be advantageous to solve problems with a large amount of labelled input data of one type that can be correlated with less

labelled data. Thanks to that, each output can be predicted using different parts of the model. In active learning, the model can ask human operators during the learning process in case of vagueness. However, it is not an approach for solving semi-supervised learning problems.

In online learning, the available data and models have to be updated directly before prediction because observations are provided over time. Also, the probability distribution of observations is expected to change over time. In the case of prescriptive maintenance, where there is new data every chosen period, it is essential not to wait until the end of the process because it can not come.

Transfer learning. There is also the possibility to use Transfer learning, where learning knowledge of an already trained machine learning model is applied to a different but related problem. Which also described situations in prescriptive maintenance when new types of machines or processes are implemented. This new data can be similar to existing information that neural network recognises but still have some differences. It can work correctly when the amount of labelled data is much higher than unlabelled. This approach can be used for institutions already using trained models for labelled data.

Semi-supervised learning. Semi-supervised learning is a good alternative to transfer learning when the amount of unlabelled data significantly exceeds already defined data. Thanks to the information from supervised learning about labelled data, it will be possible to choose the correct assumptions for unlabelled data. It can be continuity assumptions, where the smoothness assumption also yields a bias for decision boundaries in regions with low-density, cluster assumption with the use of clustering algorithms, where discrete clusters of information are much more likely to share a label or manifold assumption, where labelled and unlabelled data help avoid the problem with dimensionality and distances and densities are used for learning.

The most popular options for training semi-supervised learning are generative models, graph-based models, support vector machines in semi-supervised versions (transductive support vector machine) and Multiview models.

Generative models can be used as an extension of classification from supervised learning. Still, if assumptions based on labelled data for unlabelled are wrong, the accuracy of the solution can be lower than the one based on. Essential for it is that unlabelled data have to have distinctive parameters that are recognisable. The possibility of using this approach for part of data for the prescriptive maintenance strategy is high.

For graph-based models, there is a node for labelled and unlabelled data. For graph construction, prescriptive maintenance expert knowledge has to be used. Data forms lower-dimensional manifolds in its embedding space, and the task of a classification algorithm is to separate these tangled manifolds. The important part is creating correct nodes for labelled data, which should be based on proper expertise. The transductive support vector machine model aims to identify unlabelled data for decision boundary to achieve maximal margin overall all information. The main problem is optimisation. Example solutions can be deterministic annealing, continuation method, semi-definite programming relaxation, or stochastic gradient descent.

Multiview models use at least three different learners trained on the same labelled data but with some differences in their bias. The final prediction is based on the votes of learners. Each learner can be a black box type and can be modified independently, which can be possibly used in prescriptive maintenance cases.

Summary

The main contribution of this study to the development of the current state of the art is the proposal to choose suitable training methodologies for the neural network concerning the Prescriptive

Maintenance (RxM) strategy. This will help fill the gap in research on the use of machine learning for Prescriptive Maintenance and l allow for its further automation process. The analyses of existing research in this field with suggestions for the use of correct training algorithms for supervised and semi-supervised learning were proposed. Especially correlation between the selection of training for supervised neural networks and its influence on training for semi-supervised learning.

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