Deep learning representation pre-training for industry 4.0

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Abstract

Deep learning (DL) approaches have multiple potential advantages that have been explored in various fields, but for prognostic and health management (PHM) applications, this is not the case due to the lack of data in particular applications and also due of the absence of multiple DL-oriented benchmarks as in other fields, which limits the research in this area even though these types of applications will have a strong impact on the industrial world. To introduce the benefits of DL in this area, we should be able to develop models even when we have small data sets, to verify whether or not this is possible, in this thesis we explore the research direction of few shot learning in the context of equipment PHM.

Keywords— PHM, RUL prognostic, Deep learning, Few shot learning

1. Context

The context of this PhD is the industry of the future and more particularly the contribution of digitalization and Artificial Intelligence to predictive maintenance. Predictive maintenance is a strategy whose objective is to anticipate the failure (rather than to undergo it) with respect to the real state of a production system and forecasts on its operation. This anticipation thus makes it possible to minimize the drawbacks of traditional maintenance such as unexpected breakdowns interrupting production, lack of spare parts for repairs, to name but a few. This approach to maintenance, based on the digitalization of companies, uses the data collected to predict and forecast the evolution of degradation and propose the maintenance actions best suited to the current situation of the production system in order to anticipate failures by limiting unnecessary operations. Thus, the prognosis consists of evaluating the Remaining Useful Lifetime (RUL) of a system, for example, a component, a machine, or even a production line. This is done by predicting the future state of health of the system up to its failure based on available past/present/future information, such as history, current operating data, but also future production planning and planned maintenance actions.

The objective of this PhD is therefore to propose deep learning models for the analysis and representation of available data to make a prognosis. Data analysis is essential because although the quantity of data available in this future industry context is often important, the data relevant for prognosis can be rare (infrequent event), of uncertain quality, unlabeled, partial, unbalanced... To address this issue, the originality of the approach to be followed in this PhD is based on the pre-training of deep learning networks. Indeed, in the field of deep learning, the unsupervised learning of representations allows to exploit all available data, annotated or not, and to extract generic information transferable to all target tasks of classification and prognosis. This makes it possible to considerably reduce the size of the learning dataset for the task at hand.

While such representations have already been successfully explored in the fields of image recognition in 2014, with convolutional architectures trained on ImageNet, and automatic natural language processing in 2018, with attention models trained in particular on word prediction tasks on the internet, they do not yet exist in the industrial field, which probably explains at least in part why 'the ImageNet moment' of the industry of the future has not yet taken place. The objective of this PhD is to contribute to the construction of such an industrial data representation model, by designing models and tasks that are not necessarily directly related to a target application, but that allows to efficiently encode the richest and most generic information possible on some underlying industrial processes, such as the degradation of mechanical parts over time.

2. RUL PROGNOSTIC

Data based approaches are more and more used for RUL prognostic due to their ability to model highly nonlinear, complex and multidimensional systems. A number of deep learning (DL) techniques have been deployed in order to learn the mapping from monitored system data to their associated RUL.

In this regard, we proposed a simple yet powerful model architecture for RUL prediction, the proposed model has an MLP-LSTM-MLP architecture trained in an end-to-end manner (Chaoub, Voisin, Cerisara, & Iung, 2021). Generally, Recurrent neural networks are often used for problems involving time series data, because of their ability to process information over time. However, LSTM cells are designed to capture time dependencies but they do not have the capacity to handle complex feature processing, which has led other works in the literature to perform this task manually before the learning phase. Conversely, MLP are well fitted to perform such a task. We thus propose to feed all of the raw inputs into an MLP before the LSTM layers. The MLP will be in charge of processing the raw inputs and learning a good representation of each time frame, while the LSTM shall capture the dependencies through time of frame sequences. Then, a final regression head, composed of another MLP, predicts the RUL from these temporally smoothed representations. The proposed method was tested on the public C-MAPSS dataset (Saxena, Goebel, Simon, & Eklund, 2008). Comparisons with several state-of-the-art approaches were performed, showing that our model outperforms the others for complex datasets with multiple OCs.

3. SMALL DATASET PROBLEM

In recent years, multiple deep learning approaches have been proposed for RUL prediction. However, these models are data demanding, which is a big drawback when it comes to real industrial PHM applications.

Relevant data for prognostics are often scarce, expensive to obtain, unbalanced. Indeed, several factors can lead to such a situation like:

- most of industrial system are quite reliable by design,
- preventive maintenance makes the occurrence of failure even more rare,
- despite the monitoring of the system and huge amount of available data most of them are in good operation state,
- labelling the data is not an easy process as it is usually a manual process and requires to explore the maintenance report,
- trials to obtain run-to failure process data cannot be implemented at the line level since failure usually takes long time.

When looking in the literature, The majority of the works do not face this problem because they work on benchmarks dedicated to the development of DL models like the C-MAPSS data set or other available data set in the NASA repository (Saxena et al., 2008) or dedicated laboratory tests that usually are not able to represent the complexity and variability of situation faced with real industrial application. Indeed, in a real industrial use case, we will most likely face the case where we have a very limited number of representative trajectories, which may lead to poor generalization and performance.

To overcome this problem of insufficient data sets, there is a sub-field of machine learning called ”few-shot learning” which goal is to imitate the rapid learning ability of humans by being able to learn a new task with only a small number of labeled samples. This sub-area has received a lot of attention in recent years, multiple approaches and new benchmarks are proposed in this context.

3.1. Learning from few samples

Few-shot learning (FSL) is the problem of making predictions based on a limited number of samples (usually < 20). it can be used for regression and classification tasks. There are three main approachs in the litterature for FSL:

Data augmentation: These approaches aim to generate more samples from the few examples given, either by synthesizing new data using a generative model (Hariharan & Girshick, 2016; Iwana & Uchida, 2020), or using external knowledge or data (Jin & Rinard, 2020; Iwana & Uchida, 2020).

Metric learning: This family of approaches learns a nonlinear embedding in a metric space where a simple metric function is used to determine the output value of the new samples via proximity to the few labeled learning examples embedded in the same space.These approaches are widely used for few shot classification tasks (Vinyals, Blundell, Lillicrap, Kavukcuoglu, & Wierstra, 2016; Sung et al., 2017; Snell, Swersky, & Zemel, 2017).

Meta-learning: Also known as Learning-to-learn, These methods are trained on a set of episodes (few-shot tasks) instead of a set of object instances, with the motivation to learn a learning strategy that will allow effective adaptation to new such tasks using one or few examples (few-shot). Two big families of meta-learning methods exist in the literature, Gradient based meta learning, which goal is to find the optimal parameters of a model such that it can be easily fine-tuned on a new task (Finn, Abbeel, & Levine, 2017; Nichol, Achiam, & Schulman, 2018; Li, Zhou, Chen, & Li, 2017) and Metric meta learning approaches, which goal is combine the advantages of metric learning and meta learning (episodic learning) (Vinyals et al., 2016). These kind of approaches rely on having tasks that are close to the task at hand.

3.2. Fewshot learning possible directions for PHM

The approaches presented above are very promising. However, in the context of PHM applications, many circumstances restrain the methods we can try. Meta-learning and Metric learning approaches are difficult to apply when the data we have for episodic training or to train the embedding model, respectively, do not have identical number of input features, which is the case when we do not have the same sensors. Also, data augmentation can not work without having a strong prior on data distribution. Finally, whatever the approach chosen, having to merge data sets with large differences in the length of the sequences into the same approach is also a major problem to deal with.

An approach that can solve this problem in industry must be able to address all of the above challenges. During this period of the thesis, while studying the data sets available in the context of PHM, we are in the phase of adapting and assessing these three paradigms in order to propose an adapted approach that would make progress to solve these challenges and enable few-shot learning for PHM.

4. Conclusion

The lack of relevant industrial data for prognostic stands as barrier to achieving a more reliable and sustainable industry, while PHM of equipments has theoretically proven to be an approach to maximize profit and provide more safety for workers, its application to real-world data still remains a pressing question. During this thesis, we do research in the direction of Few shot learning, which could provide a practical solution that could be applied in real-world scenarios, with the goal of having a broad impact.

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Nomenclature

PHM	Prognostics and Health Management
MLP	Multi layer perceptron
$LSTM$	Long-short term memory
OC	Operating condition
FSL	Few shot learning

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