Master Thesis in Machine Learning for Intelligent Maintenance:

Uncertainty-driven AI methods for Prognostics and Health management

Motivation

Over the last few years, Artificial Intelligence (AI) has gained popularity in light of its unprecedented results in several engineering fields. Among these, the field of Prognostics and Health Management (PHM) is one of the main protagonists of the so-called “Industry 4.0 revolution” [1,4]. PHM methods are particularly appealing since they hold the promise to decrease the impact of failure events but also preventing their occurrence, thus significantly improving the availability level of industrial machines and reducing their maintenance costs. Machine Learning (ML) and Deep Learning (DL) are at the core of modern AI and have the potential to boost the impact of PHM methods in real-life applications.

However, in light of the safety-critical nature of PHM problems and the limited level of transparency and interpretability of modern DL techniques, more efforts are needed to make AI more trustworthy and reliable. A first important step in this direction is to design DL algorithms capable of estimating the level of confidence of their outputs, providing a probability density function over their predictions instead of simple point estimates [2]. This would guarantee a much higher level of interpretability associated with such techniques, allowing the user to better assess the quality and reliability of the AI algorithms in use.

Furthermore, uncertainty estimates can also help in identifying data instances that deviate from the type of observations already processed by the algorithm. This aspect can be particularly important in such cases where information about the data is limited, i.e. only observations corresponding to the machine working under nominal operating conditions are available. In such cases, it is reasonable to assume that higher uncertainty levels will be associated with data corresponding to anomalies in the machine behavior, be they due to a wearing process or simply to a never-observed “healthy” operating condition [7].

Task Description

In this thesis, we are interested in investigating the role of Uncertainty Quantification (UQ) in the context data-driven PHM problems. Both traditional and modern techniques [5,6,8] combining ML algorithms with uncertainty estimation will be analyzed, and their application to PHM case studies will be explored.

The first step of the project is expected to be an analysis of how different methods model uncertainty under some user-defined settings (e.g. by manually injecting noise at different levels in the data) in order to gain a better understanding of the peculiarities of each method in relation to the UQ task and the PHM desiderata. Then, more realistic problems in the contexts of anomaly detection and fault detection will be considered, and the role and potential benefits of UQ will be assessed in these new frameworks.

Depending on the progress of the thesis, a study of the evolution of uncertainty over time in the context of Remaining Useful Life (RUL) prediction tasks [3] could also be conducted. The data we are typically dealing with comprises heterogeneous multivariate time series data corresponding to sensor readings monitoring the machine's health state.

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References

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