Automated machine learning for dynamic energy management using time-series data

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Chapter 1

Introduction

1.1 Background

Time-series (i.e., temporally ordered sequences of data points from a common source) are ubiquitous. Time-series data, such as electrocardiograms, music, exchange rates, and energy consumption, is everywhere in our daily life and business world. Machine learning tasks performed on time-series data play a key role in various application domains, for example, energy consumption forecasting (Wang et al., 2019), electrocardiography (Humeau et al., 2009), crude oil price forecasting (Xiong et al., 2013), flood forecasting (Chang et al., 2007), and different engineering disciplines (e.g., software reliability engineering (Amin et al., 2013) and geotechnical engineering (Wei et al., 2021)). Energy consumption forecasting is an example and motivation for this research.

Electricity load forecasting is an important problem for the electric power industry, which can be approached as a time-series forecasting problem. Many big utility companies have their own load forecasting systems (Hong and Fan, 2016). Load forecasts are needed by other business entities as well, such as banks, insurance companies and stock trading firms. Due to its strong practical relevance and the challenges involved, load forecasting is an active field of research. Many approaches for load forecasting exist in the literature to improve the performance of forecasting models, with a focus on improving both accuracy and efficiency (Baliyan et al., 2015; Hong and Fan, 2016; Srivastava et al., 2016).

To operate and plan the system, we have to understand when, where, and how much electricity is spread throughout the system. Without accurate forecasts, we as end users may experience increasing rates, brownouts, or even blackouts. That is why load forecasting is crucial to the power industry. To predict future electrical load, we obviously need the load history. Because a large portion of the load is used for heating and cooling, we may also need weather data as typical residential loads are highly driven by weather, although some industrial loads may show patterns that are not much dependent on weather. Since consumption patterns change based on the work schedule, working hours, holidays, and special event information are also important. To improve the forecast accuracy, we can also leverage hierarchical information, such as weather and load data collected at higher frequency and more precisely specified geographical locations. Compared to classic demand or sales data, electricity demand data can be of much higher resolution temporally. For instance, many research activities today aim to forecast load utilization in 15- or even 5-minute intervals. At an accurate level, the electricity amount is typically also a function of the month of the year, day of the week, and hour of the day.

In this thesis, we study time-series forecasting approaches that can be easily used for this challenging application problem and other time-series forecasting problems. There are usually specific correlations between data points in a time-series that are temporally close to each other. In contrast, data points with a high temporal distance can often be considered to be more independent of each other. What distinguishes machine learning tasks on time-series data from other uses of machine learning is the consideration and exploitation of these dependencies.

A variety of approaches for time-series forecasting exist in the literature. Well-known examples include autoregressive moving average (ARMA) models (Box et al., 2015), multiple linear regression (MLR) models (Wang et al., 2016), support vector machines (SVMs) (Nie et al., 2012), Exponential Smoothing (ETS) models (Hoptroff, 1993), and dynamic factor models (Stock and Watson, 2011). More recently, deep learning models (e.g., LSTM, GRU (Siami-Namini et al., 2018; Zhang et al., 2017), deep probabilistic models (Alexandrov et al., 2020), graph neural networks (Wu et al., 2020b) and zero-shot learning for deep networks (Oreshkin et al., 2021)) have shown good performance on forecasting tasks.

However, creating a machine learning pipeline for time-series data analysis is difficult for many domain experts with limited machine learning expertise, due to the complexity of the data sets and the machine learning models. As broadly observed in practice, there is no single model that performs best on all possible data sets (see, e.g., Candanedo et al. (2017)). Thus, to achieve high forecasting accuracy, the machine learning pipeline has to be chosen carefully and is dependent on the task at hand.

Furthermore, it has been shown that feature engineering can significantly improve the performance of machine learning methods for time-series analysis (Christ et al., 2018).

Automated machine learning (AutoML; see, e.g., Hutter et al. (2019)) is a relatively new field that aims at optimising machine learning pipelines in an automated fashion. The main goal is to make the power of machine learning accessible to users with limited knowledge of machine learning and to reduce the effort in obtaining the best possible results. Most research in automated machine learning has focused on standard classification tasks based on tabular or image data while AutoML for tasks based on time-series data has received limited attention.

In this thesis, we investigate the use of AutoML for constructing machine learning models for time-series forecasting tasks and its application–short-term load forecasting. We aim to obtain highly accurate models fully automatically, without the need for making design choices by human experts.

1.2 Research questions

Improving AutoML, and applying it to time-series analysis and dynamic energy management is not a straightforward process. One of the challenges in AutoML for time-series forecasting is to develop advanced machine learning pipelines suitable for time-series tasks, which should be able to use the time-series features and well-suited machine learning models. The window size, which shows how many historical data points are helpful, also needs to be selected by the AutoML system. Furthermore, several additional data sources can be relevant to resolve dynamic energy management problems, such as weather and time/date data. Ideally, the pipeline should support such data sources. To address these challenges, in this thesis, we investigate the following research questions:

RQ1 What AutoML techniques are available and potentially usable for time series forecasting and other machine learning problems?

RQ2 How can AutoML techniques be used to predict the energy load for dynamic energy management?

RQ3 How can AutoML be used efficiently for single-step time-series forecasting?

RQ4 How can AutoML be used efficiently for multi-step time-series forecasting?

1.3 Outline

Following on from this introduction,

- Chapter 2 provides the reader with background information on time-series forecasting and energy management (short-term load forecasting). We show some machine learning models and statistical models that are used to solve the time-series forecasting and short-term load forecasting problems. The evaluation measures used for empirical evaluation of forecasting accuracy (i.e., MAE, MAPE, R^2, and RMSE) are also introduced in this chapter.

- Chapter 3 then gives an overview of AutoML, which is the technique we use to solve time-series forecasting problems, as presented in Baratchi et al. (2024).

- In Chapter 4, we apply AutoML techniques to the time-series application short-term load forecasting problem, as previously presented in Wang et al. (2019).

- Chapter 5 continues discussing AutoML for time-series forecasting. In this chapter, instead of one specific application, we study the more general time-series forecasting problem, as published in Wang et al. (2023).

- In Chapter 6 we extend the previously introduced AutoML algorithm to perform the multi-step forecasting task, as published in Wang et al. (2022).

- Chapter 7 concludes this thesis with a discussion of the results achieved. It further presents the answers to the posed research questions. We further discuss interesting research directions for future studies relevant to this work.

1.4 Contributions of this thesis

Parts of this work have given rise to peer-reviewed publications.

- Mitra Baratchi, Can Wang, Steffen Limmer, Jan N. van Rijn, Holger H. Hoos, Thomas Bäck, and Markus Olhofer. Automated Machine Learning: Past, Present and Future. *Artificial Intelligence Review*, 2024.

  This work provides a broad overview of the AutoML research field, including hyperparameter optimisation, neural architecture search, and automated machine learning systems. A major part of Chapter 3 is based on this work.

- Can Wang, Thomas Bäck, Holger H. Hoos, Mitra Baratchi, Steffen Limmer, and Markus Olhofer. Automated Machine Learning for Short-term Electric Load Forecasting. In *Proceedings of the IEEE Symposium Series on Computational Intelligence, Xiamen, China, December 6-9, 2019*, pages 314–321.

  This paper addresses how the short-term load forecasting problem can be resolved by AutoML. A major part of Chapter 4 is based on this work.

- Can Wang, Mitra Baratchi, Thomas Bäck, Holger H. Hoos, Steffen Limmer, and Markus Olhofer. Towards time-series-specific feature engineering in automated machine learning frameworks. *Under review at International Journal of Data Science and Analytics*, 2023.

  This work investigates using AutoML to construct machine learning models for single-step time-series forecasting tasks. Different feature extraction, window size selection, machine learning and AutoML techniques have been used to obtain highly accurate models. A major part of Chapter 5 is based on this work.

- Can Wang, Mitra Baratchi, Thomas Bäck, Holger H. Hoos, Steffen Limmer, and Markus Olhofer. Towards Time-Series Feature Engineering in Automated Machine Learning for Multi-Step-Ahead Forecasting. *Engineering Proceedings*, 18(1), 2022.

  This work presents a study of AutoML for multi-step time-series forecasting. Multi-output and recursive models are developed with AutoML techniques to resolve this task. A major part of Chapter 6 is based on this work.