LITERATURE REVIEW ON AUTOMATED MACHINE LEARNING (AUTOML)

Seminar paper

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Abstract

AutoML automated machine learning (ML). Machine learning techniques are finding an application in more and more fields and companies. Experts are supported and users with little experience can now be addressed. In this paper, 31 out of 763 publications are selected. The results are classified into the three categories: "General", "Types of AutoML" and "Technical". The keyword "General" summarises the advantages and challenges. The extent to which AutoML is automated is described in more detail in the "Types of AutoML" category, which is further subdivided into partial automation, full automation and conscious integration of people into the process. This is followed in the next category by a basic technical explanation of the process. The paper shows the relevance of AutoML for companies and the future need of research to specify issues such as transparency.

Keywords: Automated Machine Learning, partial automation, full automation, human in the loop.

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1 Introduction

Machine learning techniques have benefited from the rapid increase in the amount of data in recent years (Mullainathan and Spiess, 2017). At the same time, this creates a high demand for data scientists with good experience and distinctive knowledge. To solve this tension around the lack of experts and the high cost, automated machine learning (AutoML) has been developed (Elrahman *et al.*, 2020; Zöller and Huber, 2021).

Google's Cloud AutoML aims to enable developers with little expertise to create high-quality models within minutes. In addition, these models can be user-defined and adapted to the requirements of the company (Google Cloud, 2021a). For example, users such as Imagia describe using Cloud AutoML to search the data for indications of chronic and age-related degenerative diseases and then using this information for preventive assessment (Google Cloud, 2021b). Microsoft divides its AutoML in Azure Machine Learning directly into two categories: There are solutions for customers with no or little coding experience and those for customers with existing knowledge (Microsoft Azure, 2020). In summary, they describe their goal as: "Automated ML democratizes the machine learning model development process, and empowers its users, no matter their data science expertise, to identify an end-to-end machine learning pipeline for any problem." (Microsoft Azure, 2020).

Now that the technology is made interesting and applicable to the masses, it is also exciting for researchers further to develop and improve AutoML (Liu, 2018). For example, from 2006 to 2020, the AutoML Challenges have promoted research in various areas of automated machine learning (Escalante, 2020). Some of these challenges are sponsored by large companies, such as Google or Amazon, so that their technologies are constantly developed and new solutions are obtained (Bezrukavnikov and Linder, 2021). AutoML applications create models and solutions faster than experts can. In addition, users often benefit from better models than those created manually (Lin, 2020). Experts can also hand over tedious tasks to the machine. They can instead spend more time interpreting the model or evaluating the data, for example. This means there is an advantage for every user (Gijsbers and Vanschoren, 2021). Microsoft mentions saving time as a decisive advantage, but also the flexible solutions to problems (Microsoft Azure, 2020).

In the literature, the topic of AutoML is discussed controversially. AutoML itself is not uniformly defined in terms of the degree of automation. For some, the goal is full automation, while others describe only partial automation (Wang, Andres, *et al.*, 2021). Furthermore, new models are constantly being introduced, such as Auto-Weka (Thornton *et al.*, 2013). Each of these approaches describes its advantages and improvements over others (Swearingen *et al.*, 2017). These different models also result in various processes in detail. None of these models can be claimed to be better than all others in every situation and with every data set (Q. Wang *et al.*, 2019).

Therefore, the research question of what is the state of the art of literature on Automated Machine Learning (AutoML) will be examined. The aim of this paper is to give a first introduction to AutoML and to help managers to decide whether this approach could be interesting for their company. This paper first offers an overview of AutoML and its classification, followed by a literature review. This is followed by a literature review, in which the literature found is narrowed down in chapter three and described in more detail in chapter four. It is divided into the advantages and disadvantages in the chapter "General", the degree of automation in "Types of AutoML" and the technical process in "Technical". This is followed by a discussion in chapter five and the conclusion in chapter six.

2 Background

Within artificial intelligence and machine learning, the new trend AutoML has emerged (Joshi, 2020). The term Automated Machine Learning or AutoML for short is made up of the parts "Automated" and "Machine Learning". Machine Learning describes algorithms that learn and improve automatically from data. "Automated", on the other hand, describes manual tasks that are now performed with the help of technology. Such systems benefit from the strong growth in the amount and availability of data. This is because with a larger data set, more robust and richer decisions and insights can be obtained (Maher and Sakr, 2019; Duttaroy, 2020).

Now the question arises where the difference between machine learning and automated machine learning (AutoML) occurs. Due to the many possible uses of Machine Learning, the technology has become increasingly exciting for a wide range of application areas in recent years. However, experts are needed for the development of such methods, for example to select the training procedures. This is a very time-consuming and at the same time expensive process that has to be repeated for each application. This is exactly where AutoML steps in by making these decisions objective, data driven and automated. This method not only saves money, but also improves performance and makes machine learning accessible to many more groups of people. Now, even inexperienced users can be addressed (Hutter, Kotthoff and Vanschoren, 2019).

In addition to AutoML, other synonyms such as "AutoAI" or the phrase "automation in data science" are now also used, which are ultimately intended to describe the same phenomenon (Crisan and Fiore-Gartland, 2021). In this paper, the term AutoML will be used in the following.

3 Literature Review

This review aims to examine the relevant aspects of “Automated Machine Learning” and covers more than one research methodology, set of journals and geographic region (Webster and Watson, 2002). The following describes how relevant literature was extracted.

3.1 Databases and general approach

First, literature was searched for the main search term, "Automated Machine Learning". The database Google Scholar was used for this. After that I also used the other academic databases Springer Link, EBSCO, Wiso and arXiv, as well as the other search term “AutoML” in all the databases I used. I limited the search to English-language articles. In sorting the literature by date of publication, I was able to determine that approximately 90 percent of the literature was published from 2017. Therefore, the period is now narrowed down to 2017 onwards. This reduced the total from 763 to 725. Next, I distillated duplicate papers. This reduced the total from 725 to 637.

3.2 Selection and classification of content

The literature should be limited to the relevant literature. Next, I sorted out the literature by title. Special care was taken to ensure that the papers dealt with the topic "Automated Machine Learning" and not "Machine Learning". In addition, technical literature or literature that focuses on other topics was sorted out. For example, some literature describes a medical application. In general, many papers on AutoML systems present the results of an AutoML competition, introduce a new system, or establish a new benchmark for comparing systems.

Reason for deletion	Number of Papers after deletion
Relevant Years	725
Duplicate papers	637
Sorting by title	265
Abstract	126
Whole text	31

Table 1. Limit to the relevant literature.

3.3 Selected literature

As shown in Figure 1, most of the literature was published in the last years. It can also be seen that the topic is very relevant in 2021. Here, a lot of relevant literature on the topic has already been published within a shorter period of time.

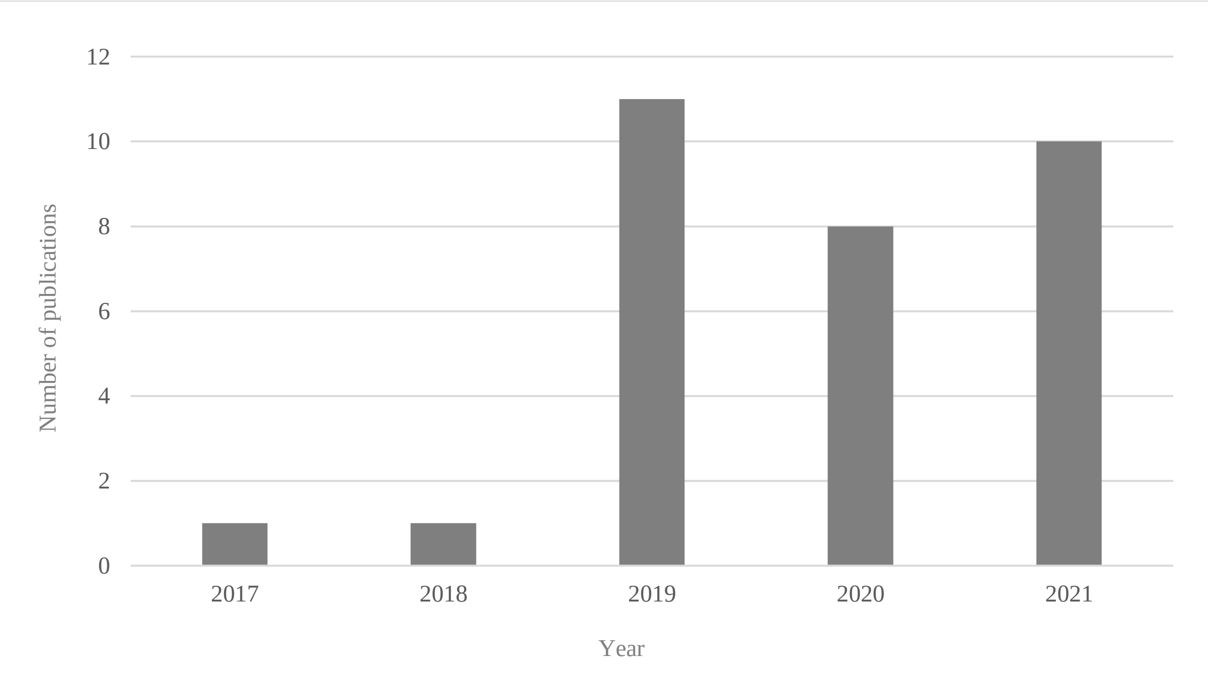

Figure 1. Selected literature sorted by date of publication.

The 31 papers that remained after careful sorting are shown in Table 1. These are divided into the three categories “General“, “Types of AutoML“ and “Technical“. “General” is further divided into “Advantages“ and “Challenges“. “Types of AutoML“, on the other hand, has been divided into “Narrow AutoML”, “Generalised AutoML” and “Human in the loop“ (HITL).

Source				General		Types of AutoML			Technical
No.	**Titel**	**Author**	**Year**	**Advantages**	**Challenges**	**Narrow**	**Generalised**	**HITL**	
2	Taking Human out of Learning Applications: A Survey on Automated Machine Learning	Yao, Q. *et al.*	2019	x	x	x	x		x
6	ATM: A distributed, collaborative, scalable system for automated machine learning	Swearingen, T. *et al.*	2017		x	x	x		
7	Automated Machine Learning: The New Wave of Machine Learning	Chauhan, K. *et al.*	2020	x	x		x		x
8	Automated Machine Learning: State-of-The-Art and Open Challenges	Elshawi, R., Maher, M. and Sakr, S.	2019	x	x	x	x		x
9	ATMSeer: Increasing Transparency and Controllability in Automated Machine Learning	Wang, Q. *et al.*	2019		x	x			x
11	Techniques for Automated Machine Learning	Chen, Y.-W., Song, Q. and Hu, X.	2021		x				x
14	Automated machine learning: Review of the state-of-the-art and opportunities for healthcare	Waring, J., Lindvall, C. and Umeton, R.	2020	x	x	x	x		x
15	Towards Automated Machine Learning: Evaluation and Comparison of AutoML Approaches and Tools	Truong, A. *et al.*	2019			x	x		x
22	Automated Machine Learning in Practice: State of the Art and Recent Results	Tuggener, L. *et al.*	2019	x		x			x
33	Automated Machine Learning -- a brief review at the end of the early years	Escalante, H. J.	2020		x	x	x		x
38	Trust in AutoML: exploring information needs for establishing trust in automated machine learning sys-tems	Drozdal, J. *et al.*	2020		x		x		
39	SmartML: A Meta Learning-Based Framework for Automated Selection and Hyperparameter Tuning for Machine Learning Algorithms	Maher, M. and Sakr, S.	2019	x		x	x		x
58	Hyperparameter Optimization	Feurer, M. and Hutter, F.	2019						x
67	Benchmark and Survey of Automated Machine Learning Frameworks	Zöller, M.-A. and Huber, M. F.	2021	x	x	x			x
97	The Automatic Statistician	Steinruecken, C. *et al.*	2019		x				x
206	GAMA: A General Automated Machine Learning Assistant	Gijsbers, P. and Vanschoren, J.	2021		x		x		x
207	An Empirical Analysis of Integrating Feature Extraction to Automated Machine Learning Pipeline	Eldeeb, H., Amashukeli, S. and El Shawi, R.	2021	x			x		x
218	Automated Machine Learning: Techniques and Frameworks	Elshawi, R. and Sakr, S.	2020	x	x	x	x		x
336	How Can Machine Learning and Optimization Help Each Other Better?	Lin, Z.-C.	2020	x	x	x			
341	AutoML: A survey of the state-of-the-art	He, X., Zhao, K. and Chu, X.	2021	x	x		x		x
359	A Very Brief and Critical Discussion on AutoML	Liu, B.	2018		x	x	x		
377	Putting the Human Back in the AutoML Loop	Xanthopoulos, I. *et al.*	2020	x	x		x	x	
382	Amazon SageMaker Autopilot: a white box AutoML solution at scale	Das, P. *et al.*	2020	x	x	x			
470	The Risks of AutoML and How to Avoid Them	Abbasi, A., Kitchens, B. and Ah-mad, F.	2019		x				
689	AutoDS: Towards Human-Centered Automation of Data Science	Wang, D., Andres, J., *et al.*	2021			x	x	x	
717	A Neophyte With AutoML: Evaluating the Promises of Automatic Machine Learning Tools	Bezrukavnikov, O. and Linder, R.	2021	x	x	x	x		
718	How Much Automation Does a Data Scientist Want?	Wang, D., Liao, Q. V., *et al.*	2021			x	x	x	
722	Fits and Starts: Enterprise Use of AutoML and the Role of Humans in the Loop	Crisan, A. and Fiore-Gartland, B.	2021		x		x	x	x
725	Whither AutoML? Understanding the Role of Automation in Machine Learning Workflows	Xin, D. *et al.*	2021	x	x	x	x	x	
736	Human-AI Collaboration in Data Science: Exploring Data Scientists' Perceptions of Automated AI	Wang, D. *et al.*	2019	x	x			x	x
749	Towards human-guided machine learning	Gil, Y. *et al.*	2019	x	x			x	

Table 2. Literature Matrix.

4 Findings

In the following, the three categories General, Types of AutoML and Technical with their respective subcategories, already described above, will be explained in more detail.

4.1 General

AutoML can be used differently depending on the expertise of the user (Xin *et al.*, 2021). There are also some challenges, including transparency and thus trust, which will be discussed below (Q. Wang *et al.*, 2019).

4.1.1 Advantages

The benefits of automated machine learning are initially dependent on the user. There are experts in this field, as well as inexperienced users. Machine learning techniques are simplified by AutoML, rendering it accessible to inexperienced people, which makes the technology accessible to the masses. It also makes them more accessible to practitioners and companies. At the same time, fewer experts are needed, which leads to cost savings (Yao *et al.*, 2019). There are advantages for these experienced users, as they can now be freed from tedious tasks (Tuggener *et al.*, 2019). At the same time, they can focus on other tasks, such as those with more application and business value (Yao *et al.*, 2019). This greatly increases the efficiency of a data scientist's work (Tuggener *et al.*, 2019).

Furthermore, AutoML increases reproducibility, improves code maintainability and facilitates knowledge exchange. This standardisation makes it easier to compare models, for example (Xin *et al.*, 2021).

Of course, AutoML also solves machine learning problems such as the lack of expensive data scientists by allowing the machine to take over tasks. This means that repetitive development costs can be saved at the same time (Das *et al.*, 2020).

4.1.2 Challenges

Transparency and trust are closely related. Many users ask themselves what the system actually did inside, and how it came to these decisions. This lack of transparency leads to a decline in trust in the systems, and users tend not to want to use AutoML in critical areas (Q. Wang *et al.*, 2019). Especially with cloud solutions, due to their black box nature, users want more customisation options. Increased user-defined control is also a big issue (Xin *et al.*, 2021). At best, the process should be transparent, auditable and customisable by the user (Xanthopoulos *et al.*, 2020). This topic is also summarised under the term "explainable AI" (Steinruecken *et al.*, 2019). In addition, various design prototypes are proposed that lead to an increase in transparency (Drozdal *et al.*, 2020). Differences between various user groups also have an effect on the degree of transparency they desire in order to trust the systems (Xin *et al.*, 2021).

Another challenge is the wide range of users (Gijsbers and Vanschoren, 2021). For example, many current tools and frameworks cannot yet be considered user-friendly for non-experts, as technical skills are still needed (Elshawi and Sakr, 2020). At the same time, a haphazard application of AutoML, with a lack of expertise, will often not be able to deliver the desired results (Abbasi, Kitchens and Ahmad, 2019).

Furthermore, there is not one model that can be classified as the best working one, but it is different for each problem (Q. Wang *et al.*, 2019). Each model claims to be better than the other. Thus, uncertainty can quickly arise about which AutoML method should be chosen from the large pool (Swearingen *et al.*, 2017).

AutoML challenges are used to try to find a solution to some of these challenges (Escalante, 2020).

4.2 Types of AutoML

AutoML is defined differently. Some authors describe the strong reduction or preferential elimination of humans by Automated Machine Learning (Elshawi, Maher and Sakr, 2019; Tuggener *et al.*, 2019). Others draw a stronger line. According to them, humans should remain a part of the whole process (Crisan and Fiore-Gartland, 2021; Xin *et al.*, 2021). The opposite side, namely the goal of automating the entire process, is also represented by some authors (He, Zhao and Chu, 2021).

This scale from "people do one part, the machine does the other" to "everything is automated" will be discussed in more detail in this chapter using specific frameworks.

4.2.1 Narrow AutoML

Narrow AutoML describes individual techniques of the process that are automated. Experts cannot be completely dispensed with (Liu, 2018). For example, a machine learning (ML) process can be roughly divided into the phases of data preprocessing, modelling and postprocessing. AutoML solutions offer different levels of support for each of these phases (Xin *et al.*, 2021). A specific part, such as hyperparameter optimisation or model selection, is taken over by the machine. Other tasks remain correspondingly for the human. Compared to full automation, the advantage of partial automation is the reduction of computational effort. A qualified expert can quickly determine the hyperparameters based on his experience and thus the computational effort can be reduced (Liu, 2018).

Some software applications can take over the different steps of AutoML. These include H20 AutoML, which performs hyperparameter optimisation and model selection (Lin, 2020) with the aim of supporting data scientists (Zöller and Huber, 2021).

The best-known AutoML packages include Auto-WEKA, AutoSklearn and TPOT (Swearingen *et al.*, 2017). *Auto-WEKA* is considered the first framework for AutoML (Elshawi and Sakr, 2020). It automates algorithm selection and hyperparameter optimisation (Maher and Sakr, 2019). However, it does not provide support for critical steps such as assessing the quality of training data (Wang, Andres, *et al.*, 2021). Auto-WEKA is said to perform better than standard algorithms, especially on larger datasets (Waring, Lindvall and Umeton, 2020). *AutoSklearn* aims to solve the CASH problem (Tuggener *et al.*, 2019). For the first time, meta-learning was introduced in the initialisation of the combined algorithm selection and tuning of the hyper-parameters (Elshawi and Sakr, 2020). In addition, unlike with Auto-WEKA, the improvement took place that the models are no longer discarded after training (Swearingen *et al.*, 2017). However, problems arise with both frameworks in dealing with large clinical datasets (Waring, Lindvall and Umeton, 2020). The *Tree-based pipeline optimisation tool (TPOT)* applies feature processing, model and hyperparameters to a classification or regression task, but can also support neural networks (Tuggener *et al.*, 2019; Bezrukavnikov and Linder, 2021). TPOT is based on generic programming (Eldeeb, Amashukeli and El Shawi, 2021). It was originally developed for biomedical data science and is more flexible than many frameworks, but at the same time can be expensive (Das *et al.*, 2020; Waring, Lindvall and Umeton, 2020). In addition, the data pre-processing here must be carried out completely manually by humans (Truong *et al.*, 2019).

4.2.2 Generalised AutoML

Fully automated applications can serve to make AutoML accessible to many people. However, the individual solutions tend to be less transparent. With generalised AutoML, ideally no expert effort is required to execute the AutoML process (Liu, 2018). This leads to a democratisation of AutoML, as such models are particularly targeted at inexperienced individuals. They are now enabled to create models themselves (Crisan and Fiore-Gartland, 2021). AutoML Challenges are always taking place to drive research forward (Escalante, 2020). These include the ChaLearn AutoML Challenges in 2015-2018, which aimed to solve machine learning problems without human intervention (Waring, Lindvall and Umeton, 2020).

AI companies have also responded to this trend by developing systems and then making them publicly available. One example is Cloud AutoML by Google (He, Zhao and Chu, 2021). Other cloud providers include Microsoft Azure Automated ML and Amazon SageMaker Autopilot. These systems are less transparent and less customisable. On the other hand, they require little programming, which is good for beginners. Furthermore, they can be characterised by a payment proportionate to the computing power used, since the computing resources are provided by the provider. In the model evaluation, Google only provides general information, while Amazon and Microsoft go more into detail and present a summary of the models examined (Xin *et al.*, 2021).

The start-up DataRobot considers itself a “platform” and simultaneously a time turnkey end-to-end car ML solution. In contrast to the cloud providers, more customisation options are available here, and the technical support is more pronounced. These and similar solutions are aimed directly at business users (Drozdal *et al.*, 2020; Wang, Liao, *et al.*, 2021; Xin *et al.*, 2021). Therefore, they even offer a model interpretation (Truong *et al.*, 2019).

4.2.3 Human in the loop

While a part of the public is worried about when artificial intelligence will completely replace humans, researchers are beginning to argue that both sides should work together (Wang, Andres, *et al.*, 2021). This line of research is referred to as Human in the loop (HITL) (Wang, Liao, *et al.*, 2021).
It has been found that many users find it difficult to understand the output visualization (Wang, Liao, *et al.*, 2021). Furthermore, the lack of understanding weakens trust in the systems and their solutions (Wang, Liao, *et al.*, 2021). One solution would be for the AutoML systems to be monitored and controlled by humans without taking over every step of the process (Crisan and Fiore-Gartland, 2021). Explainability could be appointed as an important goal, which should make research and modifications easily accessible. For example, it should be stated which models were considered and why (D. Wang *et al.*, 2019).
Other results show that humans are incredibly good at supporting the difficulties of AutoML using their intuition and domain knowledge. Moreover, it is seen as crucial for the socially acceptable and effective use of machine learning methods to involve humans. That is, the goal is to relate humans and machines in the most productive way (Xin *et al.*, 2021). At the same time, the speed of AutoML, as well as the ability to interpret, weigh and refine must be balanced (Crisan and Fiore-Gartland, 2021).
Other authors go so far as to suggest that the term "AutoML" should no longer be used and instead propose mixed-initiative ML solutions (Xin *et al.*, 2021).
Surveys of data scientists show that automation is important from their point of view. Nevertheless, they see a collaboration of both groups in the future and no replacement of humans (D. Wang *et al.*, 2019). Complete automation is not even possible or desirable in certain areas. An example would be additional human knowledge that is not available in the data. Therefore, they propose the hybrid approach of human-guided machine learning (HGML). It aims to support the user to guide AutoML systems using domain knowledge (Gil *et al.*, 2019).

4.3 Technical

AutoML is a complex process that involves a series of steps (Elshawi, Maher and Sakr, 2019). The preprocessing of features, the selection of algorithms, the tuning of hyperparameters and the formation of ensembles are considered particularly challenging (Tuggener *et al.*, 2019). The pipeline of automatic machine learning is shown in Figure 2 for overview. Also delineated is which processes the AutoML system could take over (Yao *et al.*, 2019).

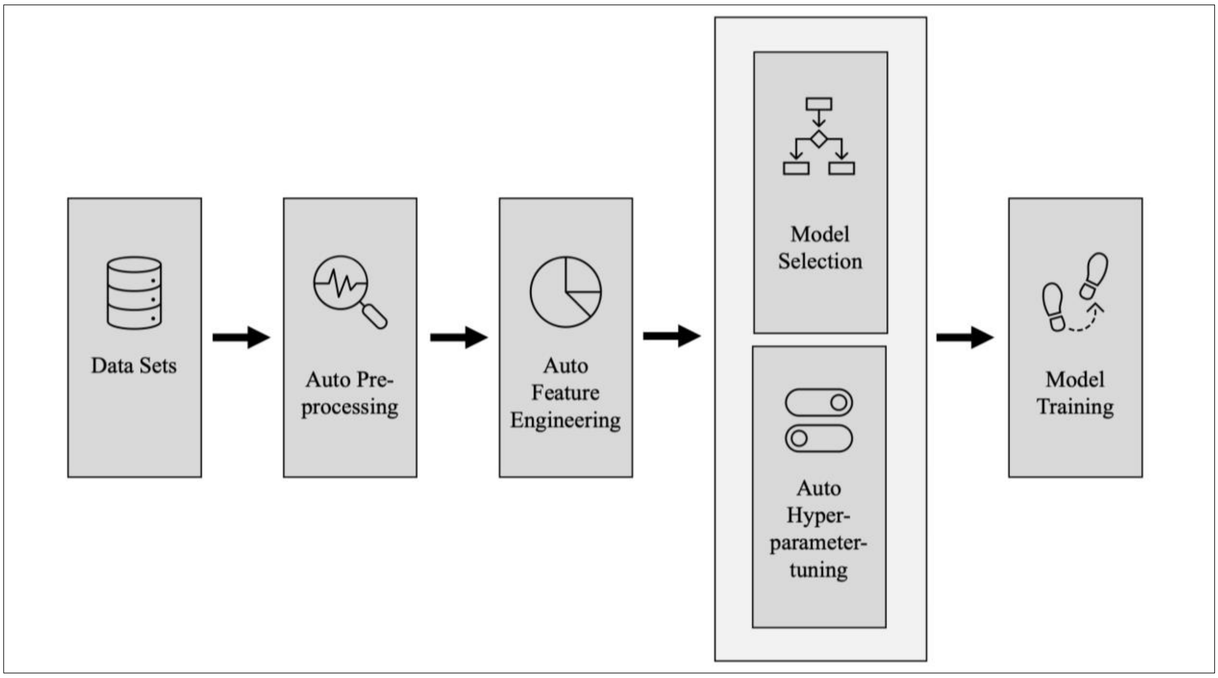

Figure 2. *Taxonomy of AutoML* (Chauhan *et al.*, 2020).

Furthermore, a distinction can be made between fixed and variable AutoML frameworks. Fixed systems are those in which a fixed pipeline structure is set. Depending on the data set, this can be sufficient because it greatly reduces complexity. For others, however, this can lead to low pipeline performance. There, flexible adaptation to the task is more appropriate, which is the characteristic of variable AutoML frameworks (Zöller and Huber, 2021). Thus, they can adapt to different user goals and data sets. Fixed systems are generally widely used; one of the first variable pipelines is TPOT (Crisan and Fiore-Gartland, 2021).

The AutoML process goes through the following categories: Data Preprocessing, Feature Engineering, and Model Building (He, Zhao and Chu, 2021).

Data preprocessing can be further divided into three sections: Data Collection, Data Cleaning, and Data Enhancement. Data collection is necessary to create a new data set. Data cleaning, on the other hand, ensures that noisy data do not negatively affect the subsequent model training. Data cleaning ensures higher model robustness and improved model performance (He, Zhao and Chu, 2021). The data pre-processing phase leads to the delivery of quality data and is therefore a crucial part of the pipeline. However, many data scientists perceive this task as mundane or boring (Chauhan *et al.*, 2020).

Feature engineering ensures that subsequent learning tools can perform well. To do this, automatic explanatory variables called features are generated from the data (Yao *et al.*, 2019; Waring, Lindvall and Umeton, 2020). This can also be considered a critical process, as the appropriateness of the features directly affects model performance (Chen, Song and Hu, 2021; Zöller and Huber, 2021). It is a very complex task, considered by top data scientists to be the most time-consuming step (Eldeeb, Amashukeli and El Shawi, 2021). Feature engineering can be split into three phases: Feature mining, feature generation and feature selection. In feature mining, the meaningful features are selected from a set of all features. These are then combined with existing features, which is an iterative process called feature generation. How often this is repeated influences the feature selection. For example, the loss of the model when including or excluding a feature for selection is measured (Chauhan *et al.*, 2020).

Model selection is used to obtain a model for the prediction task. This is determined under the trade-off between execution time and accuracy. To finalise the model, hyperparameter optimisation is usually re-run (Chauhan *et al.*, 2020, p. 209).

Hyperparameters are settings which affect the behaviour of the algorithm in some way (Waring, Lindvall and Umeton, 2020). In AutoML, these hyperparameters can be set automatically, thereby improving performance. The advantage here is that the individual methods can thus be compared fairly with each other (Feurer and Hutter, 2019). In addition, the same or even better results can be achieved manually by experts (Waring, Lindvall and Umeton, 2020).

Other AutoML tools and methods describe the **CASH (Combined Algorithm Selection and Hyperparameter)** problem. That is, they combine the model selection and hyperparameter optimisation problem. For this, a lower level hyperparameter selects between different learning algorithms or models. Next, models are generated by optimising the model-specific hyperparameters at the level above. The best model is then selected (Chauhan *et al.*, 2020). The goal is thus to achieve the highest validation performance for the selected algorithm among the combinations of algorithm and hyperparameter (Tuggener *et al.*, 2019). The Auto-WEKA tool presented in chapter 4.2.1, for example, also works in this way (Chauhan *et al.*, 2020).

5 Discussion

This chapter will look at the similarities and differences identified in the literature and what this means for managers. In the further course, the practical implications and limitations of this paper will be discussed.

5.1 Commonalities and differences

The authors agree that in AutoML, part of the human tasks in machine learning (ML) are now taken over by the machine. Thus, the human is relieved and can occupy himself with other tasks. However, it also became clear in this paper that there are different understandings of which parts of the entire process of machine learning are automated and are thus subsumed under the term AutoML.

The different user groups, such as experts and laypersons, lead to differentiated requirements for automation, its user-friendliness and the strength of the automation. There is also disagreement about the actual goal of AutoML. On the one hand, AutoML is to be democratised, on the other, humans are to remain in the loop. The democratisation of the process aims to enable inexperienced users to use AutoML. This means that as much as possible is handed over to the computer so that the technology is easy for everyone to understand and use quickly. This is often referred to as end-to-end AutoML solution. On the other hand, the human being is seen as an important key element, who can solve part of the process better than the machine through his or her experience and knowledge. Therefore, it is argued that the human should not be replaced. Rather, he should work together with the machine and thus combine the strengths of both. This line of research is summarised several times under the term Human in the loop.

The technical structure of AutoML is also presented in different terms. Thus, in addition to the subdivision into the three elements of search space, search techniques and performance evaluation methods, there is also the subdivision into the preprocessing of features, the selection of algorithms, the tuning of hyperparameters and the formation of ensembles. Another possibility is a very rough division into the phases of data pre-processing, modelling and post-processing. Of course, all these processes have different sub-parts. For example, feature engineering is partly counted as data pre-processing or it is given a single bullet point in the process. Due to these different terminologies, it can be a challenge to define a common AutoML process. This is also reflected in the tools, which are based on different optimisation techniques. This means that there is no concrete common process in detail. AutoML can only be defined in a very superficial similar way. In detail, differences quickly become apparent.

5.2 Implications for managers

This paper gives an overview of the topic of AutoML. It is intended to enable managers in particular to familiarise themselves quickly with the subject in order to gain an overview. It is also intended to give an outlook on the way in which the hiring of employees needs to be calculated. Therefore, various research directions are addressed in which AutoML is either suitable for laypersons or experts are still needed. The paper can help to check whether such an approach could possibly be considered for the respective company.

5.3 Further research

Due to the topicality of the subject, there is a need for research in various directions. Most literature deals with technical aspects or new tools. In the practice, it would be interesting to solve the challenges of AutoML. For example, tools could be further developed that describe procedures in a transparent and easily understandable way. In addition, an overview of which tool provides the best results for which use case would be very helpful for users in the selection process. Furthermore, for the goal of democratisation, easy-to-understand overviews of the entry point for the topic, as well as for specific use cases, would be beneficial for this target group.

Some papers are critical of complete automation because valuable human knowledge would be lost. Therefore, one possibility for further research would be to replicate this added value that humans provide. For example, the learning of models from other existing models could be further refined.

There is also a need for research in the technical areas. For example, data pre-processing is partly a human task, which could be automated. The other technical steps could also be further refined or even combined into a uniform process.

5.4 Limitations

As already mentioned, automatic machine learning is a very diverse topic. However, there is few literature that does not go into technical detail or does not present a specific tool. Other elements also limit this work. First, five scientific databases were used to search the literature, so other sources were not considered. In addition, only the search terms "Automated Machine Learning" and "AutoML" were used, so other synonyms were omitted. However, at the same time, an attempt was made to compensate for this as well as possible through an iterative search. At the same time, only sources in English were considered, so that possible relevant literature was excluded. Even though an effort was made to document the selection process as precisely as possible, it was only carried out by a single person. This could limit objectivity. Furthermore, since AutoML is a very young topic where new articles are constantly being published, it is possible that the most recent articles are not included in this literature review.

6 Conclusion

In this paper, the state of the art of literature on Automated Machine Learning (AutoML) was identified. The selected literature could be divided into the areas General, Types of AutoML and Technical.

Automated machine learning can be applied by inexperienced users as well as experts. While laypersons should be given access to AutoML in the first place, experts can now occupy themselves with other tasks. So overall, it helps to lighten the load. In addition, AutoML addresses machine learning challenges by, for example, reducing the number of experts needed. However, new challenges also arise, such as the lack of transparency of the systems. This makes it difficult for some users to trust the systems. Also, with the large number of models, users can quickly lose track of which model is the most suitable.

Furthermore, AutoML systems differ in the degree of automation. Partially automated systems can only automate part of the process; other parts must still be carried out by humans or experts. In addition to H20 AutoML, these include Auto-WEKA, AutoSklearn and TPOT. Contrarily, there are also systems that aim to optimise the entire process and intend to promote the democratisation of AutoML in particular. Some examples of such systems are Cloud AutoML from Google, Microsoft Azure Automated ML and Amazon SageMaker Autopilot. Another research direction in this area is Human in the loop, which describes how humans are actively brought into the process and work together with the machine. This offers some advantages, such as that additional knowledge that is not available in the data can be included.

Technically, it is a complex process, which is defined somewhat differently. Here, the categories of data pre-processing, feature engineering and model creation were chosen. Data pre-processing ensures that high-quality data can be worked with in the further process. In the context of feature engineering, explanatory variables are automatically selected. This is followed by model selection, which provides a model for the prediction task. Hyperparameters can influence the behaviour of the algorithm. This is also combined with model selection to form the CASH problem.

AutoML is a very current research topic. This paper has attempted to give an overview of the topic to provide managers with a basic insight into whether this topic is suitable for their application area.

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