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The Technological Emergence of AutoML: A Survey of Performant Software and Applications in the Context of Industry

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The Technological Emergence of AutoML: A Survey of Performant Software and Applications in the Context of Industry

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ABSTRACT

With most technical fields, there exists a delay between fundamental academic research and practical industrial uptake. Whilst some sciences have robust and well-established processes for commercialisation, such as the pharmaceutical practice of regimented drug trials, other fields face transitory periods in which fundamental academic advancements diffuse gradually into the space of commerce and industry. For the still relatively young field of Automated/Autonomous Machine Learning (AutoML/AutonoML), that transitory period is under way, spurred on by a burgeoning interest from broader society. Yet, to date, little research has been undertaken to assess the current state of this dissemination and its uptake. Thus, this review makes two primary contributions to knowledge around this topic. Firstly, it provides

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the most up-to-date and comprehensive survey of existing AutoML tools, both open-source and commercial. Secondly, it motivates and outlines a framework for assessing whether an AutoML solution designed for real-world application is 'performant'; this framework extends beyond the limitations of typical academic criteria, considering a variety of stakeholder needs and the human-computer interactions required to service them. Thus, additionally supported by an extensive assessment and comparison of academic and commercial case-studies, this review evaluates mainstream engagement with AutoML in the early 2020s, identifying obstacles and opportunities for accelerating future uptake.

Keywords: Automated machine learning (AutoML)

1

Introduction

Societal interest in machine learning (ML), especially the subtopic of deep learning (DL), has surged within recent years. This is partially driven by the continuing success of these approaches in many application areas (Grigorescu *et al.*, 2020; Ozbayoglu *et al.*, 2020; Minaee *et al.*, 2021; Piccialli *et al.*, 2021), facilitated by both fundamental advances (Kotsiantis *et al.*, 2006; Chen and Guestrin, 2016; Singh *et al.*, 2016; Choudhary and Gianey, 2017) and the increasing availability of computational resources. Unsurprisingly, on the academic side, the field of artificial intelligence (AI) continues to dominate research outputs, as noted by the 2021 UNESCO Science Report (Schneegans *et al.*, 2021). However, it is the current level of ML engagement in industry that is truly unprecedented. For instance, the 2021 Global AI Adoption Index, commissioned by IBM, found that 80% of 5501 global businesses are either using automation software or planning to within 12 months, and 74% are exploring or deploying AI (IBM, 2021). The Gartner 2019 CIO Agenda survey, with 3000 respondents from across the globe, agrees with this trend, revealing that the proportion of firms deploying AI has increased from 10% in 2015 to 37% in 2019 (Howard and Rowsell-Jones, 2019). Similar conclusions are echoed in the 2020 McKinsey ‘State of

AI' report (McKinsey, 2020). Naturally, such a rate of mainstream permeation is also accompanied by intensifying discussions on how to use ML, and AI more broadly, in a socially responsible manner (Makridakis, 2017; Lepri *et al.*, 2018; Jobin *et al.*, 2019; Morley *et al.*, 2020; Toreini *et al.*, 2020).

Nonetheless, despite the growing desire of industry to utilise ML, talent in data science remains scarce (Pompa and Burke, 2017; Basu, Sreeradha, 2018). Both the Gartner and IBM studies agree that lack of expertise creates a barrier to AI adoption (Howard and Rowsell-Jones, 2019; IBM, 2021), especially as, by and large, ML technology still requires specialist skills to implement and employ. Worse yet, in practice, deploying ML solutions for real-world applications requires technical skills beyond the domain of data science. Any shortfall in these broader talents will also adversely affect ML engagement in industry (Australian Computer Society, 2021; Gartner, 2021). So, faced with these realities, a business may ponder: does ML really have to rely so heavily on humans? Enter 'automated machine learning' (AutoML), a research endeavour that has become particularly popular over the last decade (Elshawi *et al.*, 2019; Hutter *et al.*, 2019; Lee *et al.*, 2019; Escalante, 2020; Santu *et al.*, 2020; He *et al.*, 2021; Zöllner and Huber, 2021), striving to mechanise as many high-level ML operations as possible. The appeal of this emergent field is multi-faceted, driven by many of the same motivations that inspire automation in general. These include not just democratisation, enabling the broader public to leverage the power of ML approaches, but also efficiency boosts, redistributing the time and effort of existing talent to more valuable functions.

Notably, within the modern era of AutoML, academia has already made much progress. Admittedly, it can be challenging to contain this ever-widening field within a simple overview, and various works lean on taxonomies and categorical systems to aid this (Kedziora *et al.*, 2020; Santu *et al.*, 2020; Dong *et al.*, 2021; Khuat *et al.*, 2021). Consider then a conceptual representation of the processes that are involved in running a real-world ML application, i.e. an ML workflow, as shown in Figure 1.1. With respect to this depiction, the bulk of AutoML research has traditionally focused on automating the model-development phase. Advances in Bayesian optimisation, which continue to be employed (Klein

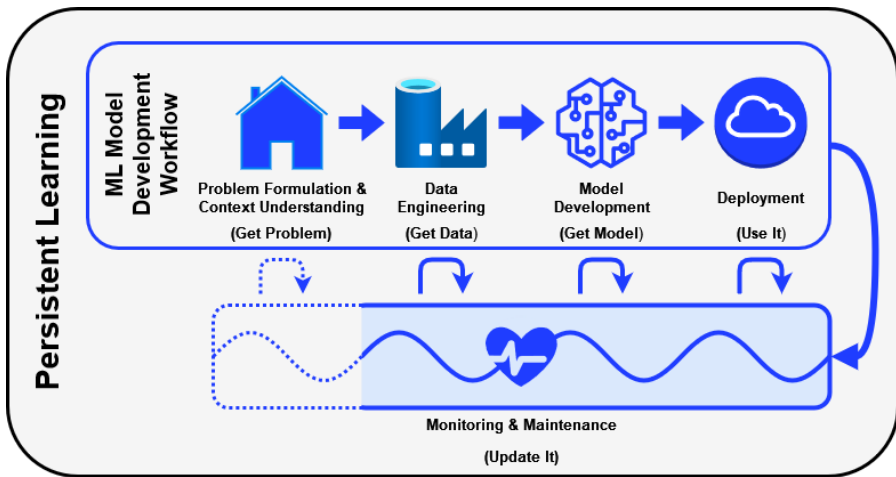


Figure 1.1: Schematic of a general machine learning (ML) workflow, which captures the phases involved in designing, constructing, deploying and maintaining an ML model for a real-world application.

et al., 2017; Frazier, 2018), are frequently credited for jump-starting this process, reducing human involvement in hyperparameter optimisation (HPO) and chipping away at the broader ‘combined algorithm selection and HPO’ (CASH) problem (Thornton *et al.*, 2013). Since then, this undertaking has evolved in many ways, such as by encapsulating neural architecture search (NAS) (Wistuba *et al.*, 2019; Ren *et al.*, 2021; Dong *et al.*, 2020a; Dong *et al.*, 2020b), which now forms the core of the AutoML-subfield known as ‘automated DL’ (AutoDL).

However, as previously hinted, the scope of AutoML – AutoDL included (Dong *et al.*, 2021) – has itself gradually expanded to encompass the rest of an ML workflow. For instance, data engineering has received its own fair share of research attention. Some works in this space focus on the initial stage of data preparation (Khayyat *et al.*, 2015), which may involve sampling and cleaning, while others contribute to the topic of automated feature engineering (AutoFE) (Lam *et al.*, 2017), covering both feature generation and selection. Then there are phase-agnostic methodologies, such as meta-learning (Ali *et al.*, 2015; Lemke *et al.*, 2015; Finn *et al.*, 2017; Vanschoren, 2018; Hutter *et al.*, 2019; Lemke and Gabrys, 2010a), that can theoretically be applied anywhere;

these continue to free humans from micro-managing ML systems and supplying domain knowledge. Of course, there is still much further to go. Automating the phase of continuous monitoring and maintenance has recently been highlighted as a crucial prerequisite for truly autonomous machine learning (AutoML) (Kedziora *et al.*, 2020), where systems persist by adapting ML models to changes in data environment (Kadlec and Gabrys, 2009a; Zliobaite *et al.*, 2012). Progress in this space remains relatively nascent (Lu *et al.*, 2019; Chen *et al.*, 2021a; Gheibi *et al.*, 2021). Additionally, rigorous efforts to survey and benchmark state-of-the-art (SOTA) algorithms and approaches (Escalante, 2020; Romano *et al.*, 2020) are relatively sparse. Nevertheless, the key takeaway from all of this is that, academically, the field of AutoML is rich with activity.

Unfortunately, the translation of pure theory to real-world practice is rarely smooth or one-to-one. That is not to suggest that AutoML has been shunned by industry; to the absolute contrary, a prior dearth of tools to assist with developing ML models – according to the IBM survey (IBM, 2021), one of the top three obstacles for AI uptake – has actually led to an explosion of commercial AutoML services. Alongside numerous open-source packages, these offerings provide businesses plenty of options to choose from, as of the early 2020s, should they wish to apply ML approaches to problems of interest. Yet a healthy scepticism remains warranted, especially where source code is confidential and promotional material is inherently biased. It cannot be assumed that AutoML algorithms and architectures, developed in experimental environments that are well-controlled and sanitised, will deliver optimal outcomes once applied within messy real-world contexts. Certainly, the academic case studies that exist (Orlenko *et al.*, 2018; Padmanabhan *et al.*, 2019; Tsiakmaki *et al.*, 2020), evaluating one or more AutoML solutions within particular industrial domains, are too few in number to make broad claims. So, it is worth asking the question: how are publicly available SOTA AutoML tools and services performing with respect to the demands of industry?

The notion of ‘performant’ ML must be central to any pioneering survey that grapples with this question. In most academic research, performance is usually gauged by purely technical metrics, such as model accuracy and training efficiency. The focus is on how well a computer,

in the absence of any human, can generate predictions/prescriptions via ML techniques. On the other hand, industrial contexts are much more human-centric, where stakeholders may have a diversity of interests and obligations; the outcomes and impact of an ML application may only be very loosely correlated with technical performance. Importantly, such matters cannot be ignored by academic AutoML researchers either, as stakeholder requirements can affect the very foundations of algorithms and architectures. For instance, a need for interpretability may force ML model-selection pools to be constrained, a focus on fairness may require mechanisms for bias mitigation, and so on.

Simply put, the technological emergence of AutoML is driven by stakeholder need and the human-computer interaction (HCI) required to service it. Correspondingly, it is impossible to gauge the current state of AutoML technology, especially in terms of whether it can support the needs of industry, without the careful development of an assessment framework anchored by a comprehensive set of HCI-weighted criteria for ‘performant ML’. Certainly, the absence of such a systematic appraisal may not only obscure future directions for progress but, if deficiencies are not identified, may also have an eventual chilling effect on technological engagement, especially in the case of unmet expectations.

With all that stated, the primary goal of this review is to present a comprehensive snapshot of how AutoML has permeated into mainstream use within the early 2020s. In contrast to two associated monographs that examined fundamental algorithms and approaches behind AutoML/AutoDL (Kedziora *et al.*, 2020; Dong *et al.*, 2021), this work surveys both their implementation and application in the context of industry. It also defines what a ‘performant’ AutoML system is – HCI support is valued highly here – and assesses how the current crop of available packages and services, as a whole, lives up to expectation. To do so in a systematic manner, this review is structured as follows. Section 2 begins by elaborating on the notion of an ML workflow, conceptually framing AutoML in terms of the high-level operations required to develop, deploy and maintain an ML model. Section 3 uses this workflow to support the introduction of industry-related stakeholders and their interests/obligations. These requirements are unified into a comprehensive set of criteria, supported by methods of assessment, that determine

whether an AutoML system can be considered performant. Section 4 then launches the survey in earnest, assessing the nature and capabilities of existing AutoML technology. This begins with an examination of open-source AutoML packages; some of these are tools dedicated to a singular purpose, e.g. HPO, while others are comprehensive systems that aim to automate a significant portion of an ML workflow. The section additionally investigates AutoML systems that are designed for specific domains, as well as commercial products. Subsequently, Section 5 assesses where AutoML technology has been used and how it has fared. Academic work focusing on real-world applications is surveyed, as are vendor-based case studies. All key findings and assessments are then synthesised in Section 6, with commentary around how mature AutoML technology is, as well as whether there are obstacles and opportunities for future uptake. Finally, Section 7 provides a concluding overview on the technological emergence of AutoML.

Appendices

A

Faded Hyperparameter Optimisation Tools

Table A.1

Name	GitHub	Ref.
Adatune	https://github.com/awslabs/adatune	Amazon Web Services, 2021a
Darts	https://github.com/quark0/darts	Liu, 2021
DeepArchitect	https://github.com/negrinho/deep_architect	Negrinho, 2021
FAR-HO	https://github.com/lucfra/FAR-HO	Franceschi, 2021
GPyOpt	https://github.com/SheffieldML/GPyOpt	The Machine Learning Group at The University of Sheffield, 2021
Optunity	https://github.com/claesenm/optunity	Claesen, 2021
Osprey	https://github.com/msmbuilder/osprey	McGibbon <i>et al.</i> , 2021
pyGPGO	https://github.com/josejimenezluna/pyGPGO	Jiménez, 2021
RoBO	https://github.com/automl/RoBO	AutoML Groups Freiburg and Hannover, 2015
sklearn-deap	https://github.com/rsteca/sklearn-deap	rsteca, 2021
Spearmint	https://github.com/HIPS/Spearmint	Harvard Intelligent Probabilistic Systems Group, 2021

B

Faded AutoML Systems

Table B.1

Name	GitHub	Company	Ref.
Adanet	https://github.com/tensorflow/adanet	Google	TensorFlow, 2021
Advisor	https://github.com/tobegit3hub/advisor	Personal	Chen, 2021
Aethos	https://github.com/Ashton-Sidhu/aethos	Personal	Sidhu, 2021
Amla	https://github.com/CiscoAI/amla	Cisco	Cisco AI, 2021
ATM	https://github.com/HDI-Project/ATM	Research	MIT - The Human Data Interaction Project, 2021
auto_ml	https://github.com/ClimbsRocks/auto_ml	Personal	Parry, 2021
Auto-Weka	https://github.com/automl/pyautoweka	Research	AutoML Groups Freiburg and Hannover, 2021c
AutoXGBoost	https://github.com/ja-thomas/autoxgboost	Personal	Thomas, 2021
DeepMining	https://github.com/sds-dubois/DeepMining	Research	Anderson, 2017; Dubois, 2017
FedNas	https://github.com/chaoyanghe/FedNAS	Research	He, 2020; He <i>et al.</i> , 2020
HpBandSter	https://github.com/automl/HpBandSter	Research	AutoML Groups Freiburg and Hannover, 2017
MetaQNN	https://github.com/bowenbaker/metaqnn	Research	Baker, 2021; Baker <i>et al.</i> , 2017
MLBox	https://github.com/AxeldeRomblay/MLBox	Personal	Romblay, 2017
Recipe	https://github.com/laic-ufmg/Recipe	Research	Laboratório de Inteligência Computacional (Computational Intelligence Lab) at Universidade Federal de Minas Gerais, 2021
tuneRanger	https://github.com/PhilippPro/tuneRanger	Research	Probst, 2021
Xcessiv	https://github.com/reiinakano/xcessiv	Research	Nakano, 2021

C

Insufficiently Detailed Commercial Systems

Table C.1

Name	Website	Ref.
Aible	https://www.aible.com/	<i>Aible</i> 2021a
Algolytics	https://algolytics.com/products/abm/	<i>Algolytics</i> 2021
DMway	http://dmway.com/	<i>DMway</i> 2021
dotData	https://dotdata.com/	<i>dotData</i> 2021
Kortical	https://kortical.com/	<i>Kortical</i> 2021
neuralstudio.ai	https://neuralstudio.ai/	<i>neuralstudio.Ai</i> 2021
OptiScorer	https://optiscorer.com/	<i>OptiScorer</i> 2021
Pecan	https://www.pecan.ai/	<i>Pecan</i> 2021
Prevision.io	https://prevision.io/	<i>Prevision.io</i> 2021
SparkCognition	https://www.sparkcognition.com/products/darwin/	<i>SparkCognition</i> 2021
TAZI	https://www.tazi.ai/	<i>TAZI</i> 2021
Xpanse	https://xpanse.ai/	<i>Xpanse</i> 2021

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