AutonoML: Towards an Integrated Framework for Autonomous Machine Learning

Other titles in Foundations and Trends® in Machine Learning

Causal Fairness Analysis: A Causal Toolkit for Fair Machine Learning
Drago Plečko and Elias Bareinboim
ISBN: 978-1-63828-330-0

A Friendly Tutorial on Mean-Field Spin Glass Techniques for Non-Physicists
Andrea Montanari and Subhabrata Sen
ISBN: 978-1-63828-212-9

Reinforcement Learning, Bit by Bit Xiuyuan Lu, Benjamin Van Roy, Vikranth Dwaracherla, Morteza Ibrahimi, Ian Osband and Zheng Wen
ISBN: 978-1-63828-254-9

Introduction to Riemannian Geometry and Geometric Statistics: From Basic Theory to Implementation with Geomstats
Nicolas Guigui, Nina Miolane and Xavier Pennec
ISBN: 978-1-63828-154-2

Graph Neural Networks for Natural Language Processing: A Survey
Lingfei Wu, Yu Chen, Kai Shen, Xiaojie Guo, Hanning Gao, Shucheng Li, Jian Pei and Bo Long
ISBN: 978-1-63828-142-9

Model-based Reinforcement Learning: A Survey
Thomas M. Moerland, Joost Broekens, Aske Plaat and Catholijn M. Jonker
ISBN: 978-1-63828-056-9

AutonoML: Towards an Integrated Framework for Autonomous Machine Learning

David Jacob Kedziora
University of Technology Sydney
david.kedziora@uts.edu.au

Katarzyna Musial
University of Technology Sydney
katarzyna.musial-gabrys@uts.edu.au

Bogdan Gabrys
University of Technology Sydney
bogdan.gabrys@uts.edu.au

the essence of knowledge
Boston — Delft

Foundations and Trends® in Machine Learning

Published, sold and distributed by:
now Publishers Inc.
PO Box 1024
Hanover, MA 02339
United States
Tel. +1-781-985-4510
www.nowpublishers.com
sales@nowpublishers.com

Outside North America:
now Publishers Inc.
PO Box 179
2600 AD Delft
The Netherlands
Tel. +31-6-51115274

The preferred citation for this publication is

D. J. Kedziora *et al.*. *AutonoML: Towards an Integrated Framework for Autonomous Machine Learning*. Foundations and Trends® in Machine Learning, vol. 17, no. 4, pp. 590–766, 2024.

ISBN: 978-1-63828-317-1

Foundations and Trends® in Machine Learning
Volume 17, Issue 4, 2024

Editorial Scope

Topics

Foundations and Trends® in Machine Learning publishes survey and tutorial articles in the following topics:

- Adaptive control and signal processing
- Applications and case studies
- Behavioral, cognitive and neural learning
- Bayesian learning
- Classification and prediction
- Clustering
- Data mining
- Dimensionality reduction
- Evaluation
- Game theoretic learning
- Graphical models
- Independent component analysis
- Inductive logic programming
- Kernel methods
- Markov chain Monte Carlo
- Model choice
- Nonparametric methods
- Online learning
- Optimization
- Reinforcement learning
- Relational learning
- Robustness
- Spectral methods
- Statistical learning theory
- Variational inference
- Visualization

Information for Librarians

Foundations and Trends® in Machine Learning, 2024, Volume 17, 6 issues. ISSN paper version 1935-8237. ISSN online version 1935-8245. Also available as a combined paper and online subscription.

Contents

AutonoML: Towards an Integrated Framework for Autonomous Machine Learning

David Jacob Kedziora[1], Katarzyna Musial[2] and Bogdan Gabrys[3]

[1] *Complex Adaptive Systems Lab, University of Technology Sydney, Australia; david.kedziora@uts.edu.au*
[2] *Complex Adaptive Systems Lab, University of Technology Sydney, Australia; katarzyna.musial-gabrys@uts.edu.au*
[3] *Complex Adaptive Systems Lab, University of Technology Sydney, Australia; bogdan.gabrys@uts.edu.au*

ABSTRACT

Over the last decade, the long-running endeavour to automate high-level processes in machine learning (ML) has risen to mainstream prominence, stimulated by advances in optimisation techniques and their impact on selecting ML models/algorithms. Central to this drive is the appeal of engineering a computational system that both discovers and deploys high-performance solutions to arbitrary ML problems with minimal human interaction. Beyond this, an even loftier goal is the pursuit of autonomy, which describes the capability of the system to independently adjust an ML solution over a lifetime of changing contexts. However, these ambitions are unlikely to be achieved in a robust manner without the broader synthesis of various mechanisms and theoretical frameworks, which, at the present time, remain scattered across numerous research threads. Accordingly, this review seeks to motivate a more expansive perspective

David Jacob Kedziora, Katarzyna Musial and Bogdan Gabrys (2024), "AutonoML: Towards an Integrated Framework for Autonomous Machine Learning", Foundations and Trends® in Machine Learning: Vol. 17, No. 4, pp 590–766. DOI: 10.1561/2200000093.

on what constitutes an automated/autonomous ML system, alongside consideration of how best to consolidate those elements. In doing so, we survey developments in the following research areas: hyperparameter optimisation, multi-component models, neural architecture search, automated feature engineering, meta-learning, multi-level ensembling, dynamic adaptation, multi-objective evaluation, resource constraints, flexible user involvement, and the principles of generalisation. We also develop a conceptual framework throughout the review, augmented by each topic, to illustrate one possible way of fusing high-level mechanisms into an autonomous ML system. Ultimately, we conclude that the notion of architectural integration deserves more discussion, without which the field of automated ML risks stifling both its technical advantages and general uptake.

1

Introduction

The field of data science is primarily concerned with the process of extracting information from data, often by way of fitting a mathematical model. Data science, as an umbrella term for techniques drawn from various disciplines, is agnostic as to who or what is driving that extraction. Indeed, while much effort has been dedicated to codifying effective workflows for data scientists (Fayyad *et al.*, 1996), e.g. the Cross-Industry Standard Process for Data Mining (CRISP-DM) (Chapman *et al.*, 2000) and others (Kurgan and Musilek, 2006; Studer *et al.*, 2021), there is no inherent restriction that forces any phase of the process to be manually applied.

Certainly, in the modern era, one element of data mining and analysis is almost ubiquitously automated: model training. At one point in time, this was considered a novel advance, with computers only just becoming capable of running model-updating algorithms, as depicted in Figure 1.1, without human intervention. In fact, this form of automation was considered such a paradigm shift that it birthed the term 'machine learning' (ML) in the 1950s (Samuel, 1959), provoked debate on its "moral and technical consequences" (Wiener, 1960; Samuel, 1960), and merged into the evolution of modern data analysis (Tukey, 1962). Advances since then, both fundamental and technological, have all but cemented computational dominance for model training.

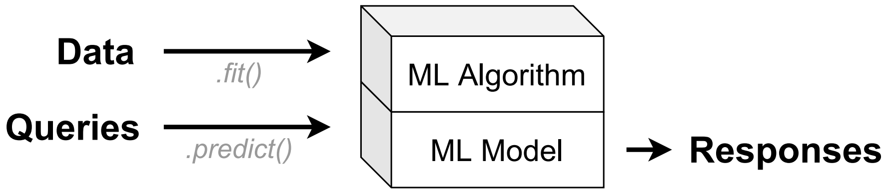

Figure 1.1: A simple representation of a machine learning (ML) model, which takes in user queries and outputs responses. The ML model is tuned by an ML algorithm, which processes training data.

Now, more than 60 years beyond the dawn of ML, associated techniques and technologies have diffused through society at large. While advances in graphics processing units (GPUs) and big data architectures are credited with popularising deep neural networks (DNNs), abundant black-box implementations of the backpropagation method have also played their part. In effect, the need for human expertise to develop complex inferential models has been lessened, and the last decade has consequently witnessed data science moving towards democratisation (Bond *et al.*, 2019). The 2012 journal article that is frequently credited with kicking off the DNN era sums it up well: "What many in the vision research community failed to appreciate was that methods that require careful hand-engineering by a programmer who understands the domain do not scale as well as methods that replace the programmer with a powerful general-purpose learning procedure." (Krizhevsky *et al.*, 2012)

Despite all this, common practice has not yet seen widespread mechanisation along the rest of the data science chain (Vega *et al.*, 2019). Granted, given a specific choice of model, it is routine to train, validate and deploy the model on clean and informative datasets with 'fit' and 'predict' functionality, depicted in Figure 1.1, that is provided by numerous coding packages. However, even within the model-development phase, the typical data scientist still has to select a model, an evaluation metric and a training/validation strategy, all subject to human bias. Once the entire ML workflow is considered, shown at high level in

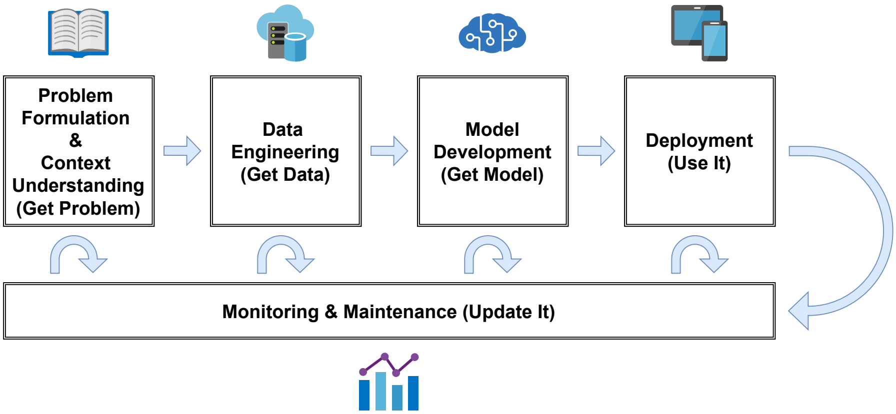

Figure 1.2: Schematic of the workflow involved in designing, constructing, deploying and maintaining an ML model. Crucially, monitoring and maintenance are required to enable continuous learning, a prerequisite for autonomous machine learning (AutonoML).

Figure 1.2, it becomes even more clear just how much an ML application relies on manual operations, which is not ideal. The data-engineering phase, for instance, is a notorious time sink for human involvement (Cios and Kurgan, 2005; Kurgan and Musilek, 2006).

The field of 'automated machine learning' (AutoML) (Hutter *et al.*, 2019; Yao *et al.*, 2018; He *et al.*, 2019; Zöller and Huber, 2021; Balaji and Allen, 2018; Truong *et al.*, 2019) has firmly established itself in recent years as a response to this; AutoML endeavours to continue mechanising the workflow of ML-based operations. It is motivated by the idea that reducing dependencies on human effort and expertise will, as a non-exhaustive list,

- make ML and its benefits more accessible to the general public,
- improve the efficiency and speed of finding ML solutions,
- improve the quality and consistency of ML solutions,
- enforce a systematic application of sound and robust ML methodologies,
- enable quick deployment and reuse of ML methodologies,

- compartmentalise complexity to reduce the potential for human error, and
- divert human resources to more productive roles.

In fairness, the field as a whole must also grapple with the risks of automation, including,

- increased obscuration of ML technical debt (Sculley *et al.*, 2015),
- inappropriate or unethical usage as a result of ML illiteracy (Bond *et al.*, 2019),
- interpretability issues in high-stakes contexts (Rudin, 2019), and
- adverse socio-economic impacts such as job displacement (Wang and Siau, 2019).

These are complex topics that are deserving of their own extensive discussions.

In this review, we focus primarily on the technical aspects of AutoML. Specifically, we motivate and discuss synthesising major threads of existing AutoML research into a general integrated framework. Unlike other published reviews, we also broaden the scope to capture adjacent research that has been, to date, barely or not at all associated with the AutoML label, particularly in recent scientific literature. In effect, the aim of this review is to help inspire the evolution of AutoML towards 'autonomous machine learning' (AutonoML), where architectures are able to independently design, construct, deploy, and maintain ML models to solve specific problems, ideally limiting human involvement to task setup and the provision of expert knowledge. That does not mean that humans should be excluded from ML-based decision making, and there is certainly a necessary debate to be had about degrees of autonomy that are appropriate in various contexts. However, for the cases where society judges the benefits of automation outweigh the disadvantages, it is worth considering how AutonoML may be achieved.

Importantly, we do not profess the optimality of any particular AutonoML architecture. Given the breadth and malleability of the field, it is unlikely that any one framework proposal will perfectly subsume all existing AutoML systems, let alone future advances. On the other hand, the merits and challenges of integration are best discussed with reference to concrete schematics. Thus, the literature survey in this monograph is accompanied by the graduated development of a conceptual framework, exemplifying the potential interplay between various elements of AutonoML. As a necessity, Section 2 lays the initial groundwork for this example architecture by considering the fundamentals of ML, abstracting and encapsulating them as the lowest level of automatic operations; this is where the 'fit' and 'predict' functionality displayed in Figure 1.1 resides.

The survey of AutoML begins in earnest within Section 3, which discusses the role of optimisation in automating the selection of an ML model/algorithm and associated hyperparameters. Section 4 then discards an assumption that the ML model need be monolithic, reviewing optimisation research for extended pipelines of data operators. This generalisation enables Section 5 to examine the optimisation of neural architectures specifically, while Section 6 focusses on the pre-processing elements of an ML pipeline, exploring the automation of feature engineering. Subsequently, Section 7 investigates how model search can be upgraded by meta-knowledge, leveraging information from external ML experiments, while Section 8 identifies the importance of ensembles and discusses how their management can be mechanised.

Notably, in terms of the ML workflow shown by Figure 1.2, the previously listed six sections focus heavily on the model-development phase – with a touch of data engineering – because this is the space in which the majority of AutoML research exists. Nonetheless, recent times have witnessed a significant broadening of scope along the entire workflow, and the next five sections document current research perspectives on the role of automation with respect to model deployment, model maintenance, and even problem formulation.

Thus, the paradigm of AutonoML is finally introduced in Section 9, defined by the ability to adapt models within dynamic contexts. This stimulates an examination within Section 10 of how the quality of any one solution should even be determined. Section 11 then examines the challenge of automating operations in low-resource settings, while Section 12 reviews efforts to reintegrate expert knowledge and user control back into autonomous systems. The survey ends with an acknowledgement in Section 13 of the drive towards one-size-fits-all AutonoML, i.e. the quest for general applicability. Finally, Section 14 concludes with a discussion on the overarching technical challenges of integration, while remaining cognisant of the fact that understanding and fostering general engagement with resulting technologies are complex endeavours in their own right.

References

5th Planning to Learn Workshop WS28 at ECAI 2012. (2012). Ed. by J. Vanschoren, P. Brazdil, and J.-U. Kietz. Citeseer.

Aalst, W. M. P. van der. (1998). "The Application of Petri Nets to Workflow Management". *Journal of Circuits, Systems and Computers*. 08(01): 21–66. DOI: 10.1142/s0218126698000043.

Abdulrahman, S. (2017). "Improving Algorithm Selection Methods using Meta-Learning by Considering Accuracy and Run Time". *PhD thesis*. Faculdade de Economia da Universidade do Porto.

Abdulrahman, S. M., A. Adamu, Y. A. Ibrahim, and A. R. Muhammad. (2017). "An Overview of the Algorithm Selection Problem". *International Journal of Computer (IJC)*. 26(1): 71–98.

Agasiev, T. and A. Karpenko. (2017). "The Program System for Automated Parameter Tuning of Optimization Algorithms". *Procedia Computer Science*. 103: 347–354. DOI: 10.1016/j.procs.2017.01.120.

Aha, D. W. (1992). "Generalizing from Case Studies: A Case Study". In: *Machine Learning Proceedings 1992*. Elsevier. 1–10. DOI: 10.1016/b978-1-55860-247-2.50006-1.

Ahn, L. von, B. Maurer, C. McMillen, D. Abraham, and M. Blum. (2008). "reCAPTCHA: Human-Based Character Recognition via Web Security Measures". *Science*. 321(5895): 1465–1468. DOI: 10.1126/science.1160379.

Alanne, K. and S. Sierla. (2022). "An overview of machine learning applications for smart buildings". *Sustainable Cities and Society*. 76: 103445. DOI: 10.1016/j.scs.2021.103445.

Alexandre, F. (2016). "Beyond Machine Learning: Autonomous Learning". In: *Proceedings of the 8th International Joint Conference on Computational Intelligence*. SCITEPRESS - Science and Technology Publications. DOI: 10.5220/0006090300970101.

Ali, A. R., M. Budka, and B. Gabrys. (2015). "A Review of Meta-level Learning in the Context of Multi-component, Multi-level Evolving Prediction Systems". en. *Tech. rep.* Bournemouth University. DOI: 10.13140/RG.2.2.32797.54243.

Ali, A. R., M. Budka, and B. Gabrys. (2019). "Towards Meta-learning of Deep Architectures for Efficient Domain Adaptation". In: *PRICAI 2019: Trends in Artificial Intelligence*. Springer International Publishing. 66–79. DOI: 10.1007/978-3-030-29911-8_6.

Ali, A. R., B. Gabrys, and M. Budka. (2018). "Cross-domain Meta-learning for Time-series Forecasting". *Procedia Computer Science*. 126: 9–18. DOI: 10.1016/j.procs.2018.07.204.

Ali, S. and K. A. Smith-Miles. (2006). "A meta-learning approach to automatic kernel selection for support vector machines". *Neurocomputing*. 70(1-3): 173–186. DOI: 10.1016/j.neucom.2006.03.004.

Ali, Y., E. Awwad, M. Al-Razgan, and A. Maarouf. (2023). "Hyperparameter Search for Machine Learning Algorithms for Optimizing the Computational Complexity". *Processes*. 11(2): 349. DOI: 10.3390/pr11020349.

Alletto, S., S. Huang, V. Francois-Lavet, Y. Nakata, and G. Rabusseau. (2020). "RandomNet: Towards Fully Automatic Neural Architecture Design for Multimodal Learning". *ArXiv*. arXiv: 2003.01181 [cs.LG].

Almeida, E., C. Ferreira, and J. Gama. (2013). "Adaptive Model Rules from Data Streams". In: *Advanced Information Systems Engineering*. Springer Berlin Heidelberg. 480–492. DOI: 10.1007/978-3-642-40988-2_31.

Alsharef, A., K. Aggarwal, Sonia, M. Kumar, and A. Mishra. (2022). "Review of ML and AutoML Solutions to Forecast Time-Series Data". *Archives of Computational Methods in Engineering*. 29(7): 5297–5311. DOI: 10.1007/s11831-022-09765-0.

Anderson, A., S. Dubois, A. Cuesta-infante, and K. Veeramachaneni. (2017). "Sample, Estimate, Tune: Scaling Bayesian Auto-Tuning of Data Science Pipelines". In: *2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE. DOI: 10.1109/dsaa.2017.82.

Anderson, A. W. (2017). "Deep Mining: scaling Bayesian auto-tuning of data science pipelines". *PhD thesis*. Massachusetts Institute of Technology.

Anderson, M. R., D. Antenucci, and M. J. Cafarella. (2016). "Runtime Support for Human-in-the-Loop Feature Engineering Systems". *IEEE Data Eng. Bull.* 39: 62–84.

Andrychowicz, M., M. Denil, S. Gómez, M. W. Hoffman, D. Pfau, T. Schaul, B. Shillingford, and N. de Freitas. (2016). "Learning to learn by gradient descent by gradient descent". In: *Advances in Neural Information Processing Systems*. Ed. by D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett. Vol. 29. Curran Associates, Inc. 3981–3989. URL: https://proceedings.neurips.cc/paper/2016/file/fb87582825f9d28a8d42c5e5e5e8b23d-Paper.pdf.

Angelov, P. and N. Kasabov. (2005). "Evolving computational intelligence systems". In: *Proceedings of the 1st international workshop on genetic fuzzy systems*. 76–82.

Anonymous. (2013). "Kaggle vs. Auto-WEKA". URL: https://www.cs.ubc.ca/~nando/540-2013/projects/p21.pdf.

Bach, S. H. and M. A. Maloof. (2008). "Paired Learners for Concept Drift". In: *2008 Eighth IEEE International Conference on Data Mining*. IEEE. DOI: 10.1109/icdm.2008.119.

Baena-Garcıa, M., J. del Campo-Ávila, R. Fidalgo, A. Bifet, R. Gavalda, and R. Morales-Bueno. (2006). "Early drift detection method". In: *Fourth international workshop on knowledge discovery from data streams*. Vol. 6. 77–86.

Bagnall, A. and G. C. Cawley. (2017). "On the Use of Default Parameter Settings in the Empirical Evaluation of Classification Algorithms". *ArXiv*. arXiv: 1703.06777v1 [cs.LG].

Bahri, M., F. Salutari, A. Putina, and M. Sozio. (2022). "AutoML: state of the art with a focus on anomaly detection, challenges, and research directions". *International Journal of Data Science and Analytics*. 14(2): 113–126. DOI: 10.1007/s41060-022-00309-0.

Baker, B., O. Gupta, N. Naik, and R. Raskar. (2017). "Designing Neural Network Architectures using Reinforcement Learning". In: *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. URL: https://openreview.net/forum?id=S1c2cvqee.

Bakirov, R., B. Gabrys, and D. Fay. (2015). "On sequences of different adaptive mechanisms in non-stationary regression problems". In: *2015 International Joint Conference on Neural Networks (IJCNN)*. IEEE. DOI: 10.1109/ijcnn.2015.7280779.

Bakirov, R., B. Gabrys, and D. Fay. (2017). "Multiple adaptive mechanisms for data-driven soft sensors". *Computers & Chemical Engineering*. 96: 42–54. DOI: 10.1016/j.compchemeng.2016.08.017.

Bakirov, R., B. Gabrys, and D. Fay. (2018). "Generic adaptation strategies for automated machine learning". *ArXiv*. arXiv: 1812.10793v2 [cs.LG].

Balaji, A. and A. Allen. (2018). "Benchmarking Automatic Machine Learning Frameworks". *ArXiv*. arXiv: 1808.06492v1 [cs.LG].

Bardenet, R., M. Brendel, B. Kégl, and M. Sebag. (2013). "Collaborative hyperparameter tuning". In: *International conference on machine learning*. 199–207.

Barreiro, E., C. R. Munteanu, M. Cruz-Monteagudo, A. Pazos, and H. González-Díaz. (2018). "Net-Net Auto Machine Learning (AutoML) Prediction of Complex Ecosystems". *Scientific Reports*. 8(1). DOI: 10.1038/s41598-018-30637-w.

Bengio, Y. (2000). "Gradient-Based Optimization of Hyperparameters". *Neural Computation*. 12(8): 1889–1900. DOI: 10.1162/089976600300015187.

Bennett, K. P., G. Kunapuli, J. Hu, and J.-S. Pang. (2008). "Bilevel Optimization and Machine Learning". In: *IEEE World Congress on Computational Intelligence*. Springer. Springer Berlin Heidelberg. 25–47. DOI: 10.1007/978-3-540-68860-0_2.

Bensusan, H. (1998). "God doesn't always shave with Occam's razor — Learning when and how to prune". In: *Machine Learning: ECML-98*. Springer Berlin Heidelberg. 119–124. DOI: 10.1007/bfb0026680.

Bergstra, J. and Y. Bengio. (2012). "Random search for hyper-parameter optimization". *Journal of machine learning research*. 13(Feb): 281–305.

Bergstra, J., B. Komer, C. Eliasmith, and D. Warde-Farley. (2014). "Preliminary evaluation of hyperopt algorithms on HPOLib". In: *ICML workshop on AutoML*.

Bergstra, J., D. Yamins, and D. Cox. (2013). "Hyperopt: A Python Library for Optimizing the Hyperparameters of Machine Learning Algorithms". In: *Proceedings of the 12th Python in Science Conference*. SciPy. DOI: 10.25080/majora-8b375195-003.

Bergstra, J. S., R. Bardenet, Y. Bengio, and B. Kégl. (2011). "Algorithms for hyper-parameter optimization". In: *Advances in neural information processing systems*. 2546–2554.

Bermúdez-Chacón, R., G. H. Gonnet, and K. Smith. (2015). "Automatic problem-specific hyperparameter optimization and model selection for supervised machine learning". en. *Tech. rep.* Zürich: ETH Zurich. DOI: 10.3929/ethz-a-010558061.

Biamonte, J., P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd. (2017). "Quantum machine learning". *Nature*. 549(7671): 195–202. DOI: 10.1038/nature23474.

Bifet, A., G. Holmes, R. Kirkby, and B. Pfahringer. (2010). "MOA: Massive online analysis". *Journal of Machine Learning Research*. 11(May): 1601–1604.

Bilalli, B. (2018). "Learning the impact of data pre-processing in data analysis". *PhD thesis*. Universitat Politècnica de Catalunya.

Bilalli, B., A. Abelló, T. Aluja-Banet, R. F. Munir, and R. Wrembel. (2018). "PRESISTANT: Data Pre-processing Assistant". In: *International Conference on Advanced Information Systems Engineering*. Springer International Publishing. 57–65. DOI: 10.1007/978-3-319-92901-9_6.

Bischl, B., G. Casalicchio, M. Feurer, F. Hutter, M. Lang, R. G. Mantovani, J. N. van Rijn, and J. Vanschoren. (2017a). "OpenML Benchmarking Suites". *ArXiv*. arXiv: 1708.03731 [stat.ML].

Bischl, B., J. Richter, J. Bossek, D. Horn, J. Thomas, and M. Lang. (2017b). "mlrMBO: A Modular Framework for Model-Based Optimization of Expensive Black-Box Functions". *ArXiv*. arXiv: 1703.03373v3 [stat.ML].

Blum, A. L. and P. Langley. (1997). "Selection of relevant features and examples in machine learning". *Artificial Intelligence*. 97(1-2): 245–271. DOI: 10.1016/s0004-3702(97)00063-5.

Bond, R., A. Koene, A. Dix, J. Boger, M. D. Mulvenna, M. Galushka, B. W. Bradley, F. Browne, H. Wang, and A. Wong. (2019). "Democratisation of Usable Machine Learning in Computer Vision". *ArXiv*. Feb. arXiv: 1902.06804v1 [cs.CV].

Bosch, S. van den. (2017). "Automatic feature generation and selection in predictive analytics solutions". *MA thesis*. Radboud University.

Bouchachia, A., B. Gabrys, and Z. Sahel. (2007). "Overview of Some Incremental Learning Algorithms". In: *2007 IEEE International Fuzzy Systems Conference*. IEEE. DOI: 10.1109/fuzzy.2007.4295640.

Brazdil, P. and C. Giraud-Carrier. (2017). "Metalearning and Algorithm Selection: progress, state of the art and introduction to the 2018 Special Issue". *Machine Learning*. 107(1): 1–14. DOI: 10.1007/s10994-017-5692-y.

Brazdil, P. B., C. Soares, and J. P. da Costa. (2003). "Ranking Learning Algorithms: Using IBL and Meta-Learning on Accuracy and Time Results". *Machine Learning*. 50(3): 251–277. DOI: 10.1023/a:1021713901879.

Brazdil, P. (1998). "Data transformation and model selection by experimentation and meta-learning". In: *Proceedings of the ECML-98 Workshop on Upgrading Learning to Meta-Level: Model Selection and Data Transformation*. 11–17.

Breiman, L. (2001). "Statistical Modeling: The Two Cultures (with comments and a rejoinder by the author)". *Statistical Science*. 16(3): 199–231. DOI: 10.1214/ss/1009213726.

Brochu, E., V. M. Cora, and N. de Freitas. (2010). "A Tutorial on Bayesian Optimization of Expensive Cost Functions, with Application to Active User Modeling and Hierarchical Reinforcement Learning". *ArXiv*. arXiv: 1012.2599v1 [cs.LG].

Brown, A. L. and M. J. Kane. (1988). "Preschool children can learn to transfer: Learning to learn and learning from example". *Cognitive Psychology*. 20(4): 493–523. DOI: 10.1016/0010-0285(88)90014-x.

Budka, M. and B. Gabrys. (2013). "Density-Preserving Sampling: Robust and Efficient Alternative to Cross-Validation for Error Estimation". *IEEE Transactions on Neural Networks and Learning Systems*. 24(1): 22–34. DOI: 10.1109/tnnls.2012.2222925.

Budka, M. and B. Gabrys. (2010). "Correntropy-based density-preserving data sampling as an alternative to standard cross-validation". In: *The 2010 International Joint Conference on Neural Networks (IJCNN)*. IEEE. DOI: 10.1109/ijcnn.2010.5596717.

Budka, M., B. Gabrys, and K. Musial. (2011). "On Accuracy of PDF Divergence Estimators and Their Applicability to Representative Data Sampling". *Entropy*. 13(7): 1229–1266. DOI: 10.3390/e13071229.

Cachada, M., S. Abdulrahman, and P. Brazdil. (2017). "Combining Feature and Algorithm Hyperparameter Selection using some Metalearning Methods". In: *AutoML@PKDD/ECML*.

Cacoveanu, S., C. Vidrighin, and R. Potolea. (2009). "Evolutional meta-learning framework for automatic classifier selection". In: *2009 IEEE 5th International Conference on Intelligent Computer Communication and Processing*. IEEE. 27–30. DOI: 10.1109/iccp.2009.5284790.

Cai, H., L. Zhu, and S. Han. (2019). "ProxylessNAS: Direct Neural Architecture Search on Target Task and Hardware". In: *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. URL: https://openreview.net/forum?id=HylVB3AqYm.

Camilleri, M., F. Neri, and M. Papoutsidakis. (2014). "An algorithmic approach to parameter selection in machine learning using meta-optimization techniques". *WSEAS Transactions on systems*. 13(2014): 202–213.

Caruana, R., A. Niculescu-Mizil, G. Crew, and A. Ksikes. (2004). "Ensemble selection from libraries of models". In: *Twenty-first international conference on Machine learning - ICML '04*. ACM Press. DOI: 10.1145/1015330.1015432.

Celik, B., P. Singh, and J. Vanschoren. (2022). "Online AutoML: an adaptive AutoML framework for online learning". *Machine Learning*. 112(6): 1897–1921. DOI: 10.1007/s10994-022-06262-0.

Celik, B. and J. Vanschoren. (2021). "Adaptation Strategies for Automated Machine Learning on Evolving Data". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. arXiv: 2006.06480v1 [cs.LG].

Chan, P. K. and S. J. Stolfo. (1993). "Experiments on multistrategy learning by meta-learning". In: *Proceedings of the second international conference on Information and knowledge management - CIKM '93*. ACM Press. DOI: 10.1145/170088.170160.

Chan, S., P. Treleaven, and L. Capra. (2013). "Continuous hyperparameter optimization for large-scale recommender systems". In: *2013 IEEE International Conference on Big Data*. IEEE. DOI: 10.1109/bigdata.2013.6691595.

Chandola, V., A. Banerjee, and V. Kumar. (2009). "Anomaly detection: A survey". *ACM Computing Surveys*. 41(3): 1–58. DOI: 10.1145/1541880.1541882.

Chapman, P., J. Clinton, R. Kerber, T. Khabaza, T. Reinartz, C. Shearer, and R. Wirth. (2000). *CRISP-DM 1.0: Step-by-step data mining guide*. SPSS.

Charnes, A., W. Cooper, and E. Rhodes. (1978). "Measuring the efficiency of decision making units". *European Journal of Operational Research*. 2(6): 429–444. DOI: 10.1016/0377-2217(78)90138-8.

Chekina, L., L. Rokach, and B. Shapira. (2011). "Meta-learning for Selecting a Multi-label Classification Algorithm". In: *2011 IEEE 11th International Conference on Data Mining Workshops*. IEEE. DOI: 10.1109/icdmw.2011.118.

Chen, B., H. Wu, W. Mo, I. Chattopadhyay, and H. Lipson. (2018). "Autostacker: A compositional evolutionary learning system". In: *Proceedings of the Genetic and Evolutionary Computation Conference - GECCO '18*. ACM Press. DOI: 10.1145/3205455.3205586.

Cheng, J. and M. S. Bernstein. (2015). "Flock: Hybrid Crowd-Machine Learning Classifiers". In: *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing - CSCW '15*. ACM Press. DOI: 10.1145/2675133.2675214.

Cheng, W., G. Kasneci, T. Graepel, D. Stern, and R. Herbrich. (2011). "Automated feature generation from structured knowledge". In: *Proceedings of the 20th ACM international conference on Information and knowledge management - CIKM '11*. ACM Press. DOI: 10.1145/2063576.2063779.

Chowdhary, M., D. Lilienthal, S. S. Saha, and K. C. Palle. (2023). "AutoML for On-Sensor Tiny Machine Learning". *IEEE Sensors Letters*. 7(11): 1–4. DOI: 10.1109/lsens.2023.3327914.

Cios, K. J. and L. A. Kurgan. (2005). "Trends in Data Mining and Knowledge Discovery". In: *Advanced Information and Knowledge Processing*. Springer London. 1–26. DOI: 10.1007/1-84628-183-0_1.

Claesen, M. and B. De Moor. (2015). "Hyperparameter search in machine learning". eng. In: vol. abs/1502.02127. 1–5. URL: https://lirias.kuleuven.be/retrieve/314688D14-188.pdf.

Clemen, R. T. (1989). "Combining forecasts: A review and annotated bibliography". *International Journal of Forecasting*. 5(4): 559–583. DOI: 10.1016/0169-2070(89)90012-5.

Cochran, D., M. Roe, C. Goudar, B. Martyn, M. Das, P. Uppuluri, S. Lennon, B. Panda, S. King, L. Dolan, *et al.* (2018). "A methodology for automated feature engineering in training of shallow neural networks for prediction of multi-linear growth failures ("Nova Algorithm")". *Technical Disclosure Commons*.

ConversionLogic. (2016). "Whitepaper: Multi-Stage Ensemble and Feature Engineering". *Tech. rep.* ConversionLogic.

Cowen-Rivers, A. I., W. Lyu, R. Tutunov, Z. Wang, A. Grosnit, R. R. Griffiths, A. M. Maraval, H. Jianye, J. Wang, J. Peters, and H. Bou-Ammar. (2022). "HEBO: An Empirical Study of Assumptions in Bayesian Optimisation". *Journal of Artificial Intelligence Research*. 74: 1269–1349. DOI: 10.1613/jair.1.13643.

Crankshaw, D., G.-E. Sela, C. Zumar, X. Mo, J. E. Gonzalez, I. Stoica, and A. Tumanov. (2018). "InferLine: ML Inference Pipeline Composition Framework". *ArXiv*. arXiv: 1812.01776v1 [cs.DC].

Cui, C., M. Hu, J. D. Weir, and T. Wu. (2016). "A recommendation system for meta-modeling: A meta-learning based approach". *Expert Systems with Applications*. 46: 33–44. DOI: 10.1016/j.eswa.2015.10.021.

Cui, H., G. R. Ganger, and P. B. Gibbons. (2018). "MLtuner: System Support for Automatic Machine Learning Tuning". *ArXiv*. arXiv: 1803.07445v1 [cs.LG].

Culotta, A., T. Kristjansson, A. McCallum, and P. Viola. (2006). "Corrective feedback and persistent learning for information extraction". *Artificial Intelligence*. 170(14-15): 1101–1122. DOI: 10.1016/j.artint.2006.08.001.

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan. (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II". *IEEE Transactions on Evolutionary Computation*. 6(2): 182–197. DOI: 10.1109/4235.996017.

Dewancker, I., M. McCourt, S. Clark, P. Hayes, A. Johnson, and G. Ke. (2016). "A strategy for ranking optimization methods using multiple criteria". In: *Workshop on Automatic Machine Learning*. 11–20.

Dey, N., A. E. Hassanien, C. Bhatt, A. S. Ashour, and S. C. Satapathy, eds. (2018). *Internet of Things and Big Data Analytics Toward Next-Generation Intelligence*. Springer International Publishing. DOI: 10.1007/978-3-319-60435-0.

Diveev, A., S. Konstantinov, and E. Sofronova. (2018). "A Comparison of Evolutionary Algorithms and Gradient-based Methods for the Optimal Control Problem". In: *2018 5th International Conference on Control, Decision and Information Technologies (CoDIT)*. IEEE. DOI: 10.1109/codit.2018.8394805.

Domhan, T., J. T. Springenberg, and F. Hutter. (2015). "Speeding up automatic hyperparameter optimization of deep neural networks by extrapolation of learning curves". In: *Twenty-Fourth International Joint Conference on Artificial Intelligence*.

Dong, X., D. J. Kedziora, K. Musial, and B. Gabrys. (2021). "Automated Deep Learning: Neural Architecture Search Is Not the End". *ArXiv*. DOI: 10.48550/ARXIV.2112.09245.

Dong, X., L. Liu, K. Musial, and B. Gabrys. (2020a). "NATS-Bench: Benchmarking NAS Algorithms for Architecture Topology and Size". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. Aug.: 1–1. DOI: 10.1109/tpami.2021.3054824.

Dong, X., M. Tan, A. W. Yu, D. Peng, B. Gabrys, and Q. V. Le. (2020b). "AutoHAS: Efficient Hyperparameter and Architecture Search". *ArXiv*. arXiv: 2006.03656 [cs.CV].

Dong, X. and Y. Yang. (2019). "Searching for a Robust Neural Architecture in Four GPU Hours". In: *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE. DOI: 10.1109/cvpr.2019.00186.

Dor, O. and Y. Reich. (2012). "Strengthening learning algorithms by feature discovery". *Information Sciences*. 189: 176–190. DOI: 10.1016/j.ins.2011.11.039.

Drori, I., Y. Krishnamurthy, R. Rampin, R. Lourenço, J. One, K. Cho, C. Silva, and J. Freire. (2018). "AlphaD3M: Machine learning pipeline synthesis". In: *AutoML Workshop at ICML*.

Drozdal, J., J. Weisz, D. Wang, G. Dass, B. Yao, C. Zhao, M. Muller, L. Ju, and H. Su. (2020). "Trust in AutoML: exploring information needs for establishing trust in automated machine learning systems". In: *Proceedings of the 25th International Conference on Intelligent User Interfaces*. ACM. 297–307. DOI: 10.1145/3377325.3377501. arXiv: 2001.06509v1 [cs.LG].

Dubois, S. (2015). "Deep mining: Copula-based hyper-parameter optimization for machine learning pipelines". *MA thesis*. École polytechnique - Massachusetts Institute of Technology.

Dunner, C., T. Parnell, K. Atasu, M. Sifalakis, and H. Pozidis. (2017). "Understanding and optimizing the performance of distributed machine learning applications on apache spark". In: *2017 IEEE International Conference on Big Data (Big Data)*. IEEE. DOI: 10.1109/bigdata.2017.8257942.

Dura-Bernal, S., B. A. Suter, P. Gleeson, M. Cantarelli, A. Quintana, F. Rodriguez, D. J. Kedziora, G. L. Chadderdon, C. C. Kerr, S. A. Neymotin, R. A. McDougal, M. Hines, G. M. Shepherd, and W. W. Lytton. (2019). "NetPyNE, a tool for data-driven multiscale modeling of brain circuits". *eLife*. 8. DOI: 10.7554/elife.44494.

Eastwood, M. and B. Gabrys. (2007). "The Dynamics of Negative Correlation Learning". *The Journal of VLSI Signal Processing Systems for Signal, Image, and Video Technology*. 49(2): 251–263. DOI: 10.1007/s11265-007-0074-5.

Eastwood, M. and B. Gabrys. (2011). "Model level combination of tree ensemble hyperboxes via GFMM". In: *2011 Eighth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*. IEEE. DOI: 10.1109/fskd.2011.6019563.

Eastwood, M. and B. Gabrys. (2012). "Generalised bottom-up pruning: A model level combination of decision trees". *Expert Systems with Applications*. 39(10): 9150–9158. DOI: 10.1016/j.eswa.2012.02.061.

Efimova, V., A. Filchenkov, and A. Shalyto. (2019). "Reinforcement-Based Simultaneous Algorithm and Its Hyperparameters Selection". In: *Communications in Computer and Information Science*. Springer International Publishing. 15–27. DOI: 10.1007/978-3-030-35400-8_2.

Eggensperger, K., M. Feurer, F. Hutter, J. Bergstra, J. Snoek, H. Hoos, and K. Leyton-Brown. (2013). "Towards an empirical foundation for assessing bayesian optimization of hyperparameters". In: *NIPS workshop on Bayesian Optimization in Theory and Practice*. Vol. 10. 3.

Eggensperger, K., F. Hutter, H. Hoos, and K. Leyton-Brown. (2015). "Efficient benchmarking of hyperparameter optimizers via surrogates". In: *Twenty-Ninth AAAI Conference on Artificial Intelligence*.

Elsken, T., J. H. Metzen, and F. Hutter. (2019). "Neural Architecture Search: A Survey". *Journal of Machine Learning Research*. 20(55): 1–21. URL: http://jmlr.org/papers/v20/18-598.html.

Erickson, N., J. Mueller, A. Shirkov, H. Zhang, P. Larroy, M. Li, and A. Smola. (2020). "AutoGluon-Tabular: Robust and Accurate AutoML for Structured Data". *ArXiv*. Mar. arXiv: 2003.06505v1 [stat.ML].

Escalante, H. J., M. Montes, and L. E. Sucar. (2009). "Particle Swarm Model Selection". *J. Mach. Learn. Res.* 10: 405–440.

Fakoor, R., J. Mueller, N. Erickson, P. Chaudhari, and A. J. Smola. (2020). "Fast, Accurate, and Simple Models for Tabular Data via Augmented Distillation". *Advances in Neural Information Processing Systems*. 33. arXiv: 2006.14284v1 [cs.LG].

Falkner, S., A. Klein, and F. Hutter. (2017). "Combining hyperband and bayesian optimization". In: *Proceedings of the 31st Conference on Neural Information Processing Systems (NIPS), Bayesian Optimization Workshop*.

Fang, M., Y. Li, and T. Cohn. (2017). "Learning how to Active Learn: A Deep Reinforcement Learning Approach". In: *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics. DOI: 10.18653/v1/d17-1063.

Farmer, J., N. H. Packard, and A. S. Perelson. (1986). "The immune system, adaptation, and machine learning". *Physica D: Nonlinear Phenomena*. 22(1-3): 187–204. DOI: 10.1016/0167-2789(86)90240-x.

Fayyad, U., G. Piatetsky-Shapiro, and P. Smyth. (1996). "The KDD process for extracting useful knowledge from volumes of data". *Communications of the ACM*. 39(11): 27–34. DOI: 10.1145/240455.240464.

Fernández, S., T. de la Rosa, F. Fernández, R. Suárez, J. Ortiz, D. Borrajo, and D. Manzano. (2013). "Using automated planning for improving data mining processes". *The Knowledge Engineering Review*. 28(2): 157–173. DOI: 10.1017/s0269888912000409.

Feurer, M., K. Eggensperger, S. Falkner, M. Lindauer, and F. Hutter. (2022). "Auto-Sklearn 2.0: Hands-Free AutoML via Meta-Learning". *J. Mach. Learn. Res.* 23(1).

Feurer, M., A. Klein, K. Eggensperger, J. Springenberg, M. Blum, and F. Hutter. (2015a). "Efficient and Robust Automated Machine Learning". In: *Advances in Neural Information Processing Systems 28*. Ed. by C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett. Curran Associates, Inc. 2962–2970. URL: http://papers.nips.cc/paper/5872-efficient-and-robust-automated-machine-learning.pdf.

Feurer, M., A. Klein, K. Eggensperger, J. T. Springenberg, M. Blum, and F. Hutter. (2019). "Auto-sklearn: Efficient and Robust Automated Machine Learning". In: *Automated Machine Learning*. Springer International Publishing. 113–134. DOI: 10.1007/978-3-030-05318-5_6.

Feurer, M., J. T. Springenberg, and F. Hutter. (2015b). "Initializing bayesian hyperparameter optimization via meta-learning". In: *Twenty-Ninth AAAI Conference on Artificial Intelligence*.

Finn, C., P. Abbeel, and S. Levine. (2017a). "Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks". In: *Proceedings of the 34th International Conference on Machine Learning - Volume 70. ICML'17*. Sydney, NSW, Australia: JMLR.org. 1126–1135.

Finn, C., T. Yu, T. Zhang, P. Abbeel, and S. Levine. (2017b). "One-Shot Visual Imitation Learning via Meta-Learning". In: *Proceedings of the 1st Annual Conference on Robot Learning*. Ed. by S. Levine, V. Vanhoucke, and K. Goldberg. Vol. 78. *Proceedings of Machine Learning Research*. PMLR. 357–368. URL: http://proceedings.mlr.press/v78/finn17a.html.

Fonseca, P., J. Mendoza, J. Wainer, J. Ferrer, J. Pinto, J. Guerrero, and B. Castaneda. (2015). "Automatic breast density classification using a convolutional neural network architecture search procedure". In: *Medical Imaging 2015: Computer-Aided Diagnosis*. Ed. by L. M. Hadjiiski and G. D. Tourassi. SPIE. DOI: 10.1117/12.2081576.

Fowers, J., K. Ovtcharov, M. Papamichael, T. Massengill, M. Liu, D. Lo, S. Alkalay, M. Haselman, L. Adams, M. Ghandi, S. Heil, P. Patel, A. Sapek, G. Weisz, L. Woods, S. Lanka, S. K. Reinhardt, A. M. Caulfield, E. S. Chung, and D. Burger. (2018). "A Configurable Cloud-Scale DNN Processor for Real-Time AI". In: *2018 ACM/IEEE 45th Annual International Symposium on Computer Architecture (ISCA)*. IEEE. DOI: 10.1109/isca.2018.00012.

Fu, Y., W. Chen, H. Wang, H. Li, Y. Lin, and Z. Wang. (2020). "AutoGAN-Distiller: Searching to Compress Generative Adversarial Networks". In: *Proceedings of the 37th International Conference on Machine Learning*. Ed. by H. D. III and A. Singh. Vol. 119. *Proceedings of Machine Learning Research*. Virtual: PMLR. 3292–3303. URL: http://proceedings.mlr.press/v119/fu20b.html.

Fulcher, B. D. and N. S. Jones. (2014). "Highly Comparative Feature-Based Time-Series Classification". *IEEE Transactions on Knowledge and Data Engineering*. 26(12): 3026–3037. DOI: 10.1109/tkde.2014.2316504.

Fürnkranz, J. and J. Petrak. (2001). "An evaluation of landmarking variants". In: *Working Notes of the ECML/PKDD 2000 Workshop on Integrating Aspects of Data Mining, Decision Support and Meta-Learning*. 57–68.

Gabrys, B. (2002). "Combining neuro-fuzzy classifiers for improved generalisation and reliability". In: *Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No.02CH37290)*. IEEE. DOI: 10.1109/ijcnn.2002.1007519.

Gabrys, B. (2004). "Learning hybrid neuro-fuzzy classifier models from data: to combine or not to combine?" *Fuzzy Sets and Systems*. 147(1): 39–56. DOI: 10.1016/j.fss.2003.11.010.

Gabrys, B. and A. Bargiela. (1999). "Neural Networks Based Decision Support in Presence of Uncertainties". *Journal of Water Resources Planning and Management*. 125(5): 272–280. DOI: 10.1061/(asce)0733-9496(1999)125:5(272).

Gabrys, B., K. Leiviskä, and J. Strackeljan, eds. (2005). *Do Smart Adaptive Systems Exist?* Springer Berlin Heidelberg. DOI: 10.1007/3-540-32374-0.

Gabrys, B. and D. Ruta. (2006). "Genetic algorithms in classifier fusion". *Applied Soft Computing*. 6(4): 337–347. DOI: 10.1016/j.asoc.2005.11.001.

Gama, J., P. Medas, G. Castillo, and P. Rodrigues. (2004). "Learning with Drift Detection". In: *Advances in Artificial Intelligence – SBIA 2004*. Springer Berlin Heidelberg. 286–295. DOI: 10.1007/978-3-540-28645-5_29.

Gama, J., I. Žliobaitė, A. Bifet, M. Pechenizkiy, and A. Bouchachia. (2014). "A survey on concept drift adaptation". *ACM Computing Surveys*. 46(4): 1–37. DOI: 10.1145/2523813.

Ganin, Y. and V. Lempitsky. (2015). "Unsupervised Domain Adaptation by Backpropagation". In: *Proceedings of the 32nd International Conference on Machine Learning*. Ed. by F. Bach and D. Blei. Vol. 37. *Proceedings of Machine Learning Research*. Lille, France: PMLR. 1180–1189. URL: http://proceedings.mlr.press/v37/ganin15.html.

Garciarena, U., A. Mendiburu, and R. Santana. (2018a). "Towards a more efficient representation of imputation operators in TPOT". *ArXiv*. arXiv: 1801.04407v1 [cs.LG].

Garciarena, U., R. Santana, and A. Mendiburu. (2017). "Evolving imputation strategies for missing data in classification problems with TPOT". *ArXiv*. arXiv: 1706.01120v2 [cs.LG].

Garciarena, U., R. Santana, and A. Mendiburu. (2018b). "Analysis of the Complexity of the Automatic Pipeline Generation Problem". In: *2018 IEEE Congress on Evolutionary Computation (CEC)*. IEEE. DOI: 10.1109/cec.2018.8477662.

Garouani, M., A. Ahmad, M. Bouneffa, M. Hamlich, G. Bourguin, and A. Lewandowski. (2022). "Towards big industrial data mining through explainable automated machine learning". *The International Journal of Advanced Manufacturing Technology*. 120(1-2): 1169–1188. DOI: 10.1007/s00170-022-08761-9.

Gashler, M., C. Giraud-Carrier, and T. Martinez. (2008). "Decision Tree Ensemble: Small Heterogeneous Is Better Than Large Homogeneous". In: *2008 Seventh International Conference on Machine Learning and Applications*. IEEE. DOI: 10.1109/icmla.2008.154.

Gelernter, D. (1991). *Mirror worlds: or the day software puts the universe in a shoebox—how it will happen and what it will mean*. New York: Oxford University Press.

Geman, S., E. Bienenstock, and R. Doursat. (1992). "Neural Networks and the Bias/Variance Dilemma". *Neural Computation*. 4(1): 1–58. DOI: 10.1162/neco.1992.4.1.1.

Gemert, T. v. (2017). "On the influence of dataset characteristics on classifier performance". *B.S. thesis*. Utrecht University.

Gemp, I., G. Theocharous, and M. Ghavamzadeh. (2017). "Automated data cleansing through meta-learning". In: *Twenty-Ninth IAAI Conference*.

Gencoglu, O., M. van Gils, E. Guldogan, C. Morikawa, M. Süzen, M. Gruber, J. Leinonen, and H. Huttunen. (2019). "HARK Side of Deep Learning – From Grad Student Descent to Automated Machine Learning". *ArXiv*. Apr. arXiv: 1904.07633v1 [cs.LG].

Gennatas, E. D., J. H. Friedman, L. H. Ungar, R. Pirracchio, E. Eaton, L. G. Reichmann, Y. Interian, J. M. Luna, C. B. Simone, A. Auerbach, E. Delgado, M. J. van der Laan, T. D. Solberg, and G. Valdes. (2020). "Expert-augmented machine learning". *Proceedings of the National Academy of Sciences*. 117(9): 4571–4577. DOI: 10.1073/pnas.1906831117.

Gerdes, M., D. Galar, and D. Scholz. (2016). "Automated parameter optimization for feature extraction for condition monitoring". In: *14th IMEKO TC10 Workshop on Technical Diagnostics 2016: New Perspectives in Measurements, Tools and Techniques for Systems Reliability, Maintainability and Safety, Milan, Italy, 27-28 June 2016*. 452–457.

Gijsbers, P., E. LeDell, J. Thomas, S. Poirier, B. Bischl, and J. Vanschoren. (2019). "An Open Source AutoML Benchmark". *ArXiv*. July. arXiv: 1907.00909v1 [cs.LG].

Gijsbers, P. and J. Vanschoren. (2019). "GAMA: Genetic Automated Machine learning Assistant". *Journal of Open Source Software*. 4(33): 1132. DOI: 10.21105/joss.01132.

Gil, Y., J. Honaker, S. Gupta, Y. Ma, V. D'Orazio, D. Garijo, S. Gadewar, Q. Yang, and N. Jahanshad. (2019). "Towards human-guided machine learning". In: *Proceedings of the 24th International Conference on Intelligent User Interfaces*. ACM. DOI: 10.1145/3301275.3302324.

Glazer, A. and S. Markovitch. (2013). "Resource-Bounded Selection of Learning Algorithms". *Tech. rep.* Computer Science Department, Technion.

Gomes, T. A., R. B. Prudêncio, C. Soares, A. L. Rossi, and A. Carvalho. (2012). "Combining meta-learning and search techniques to select parameters for support vector machines". *Neurocomputing*. 75(1): 3–13. DOI: 10.1016/j.neucom.2011.07.005.

Gong, X., S. Chang, Y. Jiang, and Z. Wang. (2019). "AutoGAN: Neural Architecture Search for Generative Adversarial Networks". In: *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*. IEEE. DOI: 10.1109/iccv.2019.00332.

Grabczewski, K. and N. Jankowski. (2007). "Versatile and Efficient Meta-Learning Architecture: Knowledge Representation and Management in Computational Intelligence". In: *2007 IEEE Symposium on Computational Intelligence and Data Mining*. IEEE. DOI: 10.1109/cidm.2007.368852.

Grąbczewski, K. (2014). *Meta-Learning in Decision Tree Induction*. Springer International Publishing. DOI: 10.1007/978-3-319-00960-5.

Guyon, I., I. Chaabane, H. J. Escalante, S. Escalera, D. Jajetic, J. R. Lloyd, N. Macià, B. Ray, L. Romaszko, M. Sebag, A. Statnikov, S. Treguer, and E. Viegas. (2016). "A brief review of the ChaLearn AutoML challenge: any-time any-dataset learning without human intervention". In: *Workshop on Automatic Machine Learning*. 21–30.

Guyon, I., A. Saffari, G. Dror, and G. Cawley. (2010). "Model selection: Beyond the bayesian/frequentist divide". *Journal of Machine Learning Research*. 11(Jan): 61–87.

Guyon, I., A. Saffari, G. Dror, and G. Cawley. (2011). "Challenges in Data Representation, Model Selection, and Performance Prediction". In: *Hands-On Pattern Recognition Challenges in Machine Learning, Volume 1*. Microtome Publishing USA. Chap. 1.

H2O.ai. (2017). *H2O AutoML*. URL: http://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html.

Hajian, S., F. Bonchi, and C. Castillo. (2016). "Algorithmic Bias: From Discrimination Discovery to Fairness-aware Data Mining". In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM. DOI: 10.1145/2939672.2945386.

Hall, P. M., D. Marshall, and R. R. Martin. (1998). "Incremental Eigenanalysis for Classification". In: *Proceedings of the British Machine Vision Conference 1998*. British Machine Vision Association. DOI: 10.5244/c.12.29.

Hansing, T., M. M. Krell, and F. Kirchner. (2016). "hyperSPACE: Automated Optimization of Complex Processing Pipelines for pySPACE". In: *NIPS Workshop on Bayesian Optimization. NIPS Workshop on Bayesian Optimization (BayesOPT2016), December 5-10, Barcelona, Spain*.

Hanussek, M., M. Blohm, and M. Kintz. (2020). "Can AutoML outperform humans? An evaluation on popular OpenML datasets using AutoML Benchmark". *ArXiv*. Sept. arXiv: 2009.01564 [cs.LG].

Harlap, A., D. Narayanan, A. Phanishayee, V. Seshadri, N. Devanur, G. Ganger, and P. Gibbons. (2018). "PipeDream: Fast and Efficient Pipeline Parallel DNN Training". *ArXiv*. arXiv: 1806.03377v1 [cs.DC].

He, C., M. Annavaram, and S. Avestimehr. (2020). "FedNAS: Federated Deep Learning via Neural Architecture Search". *ArXiv*. Apr. arXiv: 2004.08546 [cs.LG].

He, K., X. Zhang, S. Ren, and J. Sun. (2014). "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". In: *Computer Vision – ECCV 2014*. Springer International Publishing. 346–361. DOI: 10.1007/978-3-319-10578-9_23.

He, K., X. Zhang, S. Ren, and J. Sun. (2016). "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE. DOI: 10.1109/cvpr.2016.90.

He, X., K. Zhao, and X. Chu. (2019). "AutoML: A survey of the state-of-the-art". *Knowledge-Based Systems*. 212(Aug.): 106622. DOI: 10.1016/j.knosys.2020.106622. arXiv: 1908.00709 [cs.LG].

Heaton, J. T. (2017). "Automated Feature Engineering for Deep Neural Networks with Genetic Programming". *PhD thesis*. College of Engineering and Computing, Nova Southeastern University.

Hennig, P. and C. J. Schuler. (2012). "Entropy Search for Information-Efficient Global Optimization". *J. Mach. Learn. Res.* 13(null): 1809–1837.

Hertel, L., J. Collado, P. J. Sadowski, and P. Baldi. (2018). "Sherpa: Hyperparameter Optimization for Machine Learning Models". In: *32nd Conference on Neural Information Processing Systems (NIPS 2018)*.

Ho, T. K. and M. Basu. (2002). "Complexity measures of supervised classification problems". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 24(3): 289–300. DOI: 10.1109/34.990132.

Hoffman, M., B. Shahriari, and N. Freitas. (2014). "On correlation and budget constraints in model-based bandit optimization with application to automatic machine learning". In: *Artificial Intelligence and Statistics*. 365–374.

Hofmann, M. and R. Klinkenberg. (2016). *RapidMiner: Data mining use cases and business analytics applications*. CRC Press.

Hollmann, N., S. Müller, and F. Hutter. (2023). "Large Language Models for Automated Data Science: Introducing CAAFE for Context-Aware Automated Feature Engineering". *ArXiv*. DOI: 10.48550/ARXIV.2305.03403.

Hoos, H. H., F. Neumann, and H. Trautmann. (2017). "Automated Algorithm Selection and Configuration (Dagstuhl Seminar 16412)". *Dagstuhl Reports*. 6(10): 33–74. Ed. by H. H. Hoos, F. Neumann, and H. Trautmann. DOI: 10.4230/DagRep.6.10.33.

Horn, D., T. Wagner, D. Biermann, C. Weihs, and B. Bischl. (2015). "Model-Based Multi-objective Optimization: Taxonomy, Multi-Point Proposal, Toolbox and Benchmark". In: *Lecture Notes in Computer Science*. Springer International Publishing. 64–78. DOI: 10.1007/978-3-319-15934-8_5.

Hoste, V., I. Hendrickx, W. Daelemans, and A. van den Bosch. (2002). "Parameter optimization for machine-learning of word sense disambiguation". *Natural Language Engineering*. 8(4): 311–325. DOI: 10.1017/s1351324902003005.

Hu, H., J. Langford, R. Caruana, E. Horvitz, and D. Dey. (2018). "Macro Neural Architecture Search Revisited". In: *2nd Workshop on Meta-Learning at NeurIPS*.

Hu, Y.-J. and S.-W. Huang. (2017). "Challenges of automated machine learning on causal impact analytics for policy evaluation". In: *2017 2nd International Conference on Telecommunication and Networks (TEL-NET)*. IEEE. DOI: 10.1109/tel-net.2017.8343571.

Hutter, F., H. H. Hoos, K. Leyton-Brown, and T. Stuetzle. (2009a). "ParamILS: An Automatic Algorithm Configuration Framework". *Journal of Artificial Intelligence Research*. 36: 267–306. DOI: 10.1613/jair.2861.

Hutter, F., T. Bartz-Beielstein, H. H. Hoos, K. Leyton-Brown, and K. P. Murphy. (2010). "Sequential Model-Based Parameter Optimization: an Experimental Investigation of Automated and Interactive Approaches". In: *Experimental Methods for the Analysis of Optimization Algorithms*. Springer Berlin Heidelberg. 363–414. DOI: 10.1007/978-3-642-02538-9_15.

Hutter, F., H. Hoos, and K. Leyton-Brown. (2014a). "An Efficient Approach for Assessing Hyperparameter Importance". In: *Proceedings of the 31st International Conference on Machine Learning*. Ed. by E. P. Xing and T. Jebara. Vol. 32. *Proceedings of Machine Learning Research*. No. 1. Bejing, China: PMLR. 754–762. URL: http://proceedings.mlr.press/v32/hutter14.html.

Hutter, F., H. H. Hoos, and K. Leyton-Brown. (2011). "Sequential Model-Based Optimization for General Algorithm Configuration". In: *International conference on learning and intelligent optimization*. Springer Berlin Heidelberg. 507–523. DOI: 10.1007/978-3-642-25566-3_40.

Hutter, F., H. H. Hoos, K. Leyton-Brown, and K. P. Murphy. (2009b). "An experimental investigation of model-based parameter optimisation: SPO and beyond". In: *Proceedings of the 11th Annual conference on Genetic and evolutionary computation - GECCO '09*. ACM Press. DOI: 10.1145/1569901.1569940.

Hutter, F., L. Kotthoff, and J. Vanschoren, eds. (2019). *Automated Machine Learning: Methods, Systems, Challenges*. Springer International Publishing. DOI: 10.1007/978-3-030-05318-5.

Hutter, F., J. Lücke, and L. Schmidt-Thieme. (2015). "Beyond Manual Tuning of Hyperparameters". *KI - Künstliche Intelligenz*. 29(4): 329–337. DOI: 10.1007/s13218-015-0381-0.

Hutter, F., L. Xu, H. H. Hoos, and K. Leyton-Brown. (2014b). "Algorithm runtime prediction: Methods & evaluation". *Artificial Intelligence*. 206: 79–111. DOI: 10.1016/j.artint.2013.10.003.

Imbrea, A. (2020). "An empirical comparison of automated machine learning techniques for data streams". URL: http://essay.utwente.nl/80548/.

Jamieson, K. and A. Talwalkar. (2016). "Non-stochastic Best Arm Identification and Hyperparameter Optimization". In: *Proceedings of the 19th International Conference on Artificial Intelligence and Statistics*. Ed. by A. Gretton and C. C. Robert. Vol. 51. *Proceedings of Machine Learning Research*. Cadiz, Spain: PMLR. 240–248. URL: http://proceedings.mlr.press/v51/jamieson16.html.

Jankowski, N., W. Duch, and K. Grąbczewski. (2011). *Meta-learning in computational intelligence*. Vol. 358. Springer.

Jankowski, N. and K. Grabczewski. (2008). "Building meta-learning algorithms basing on search controlled by machine complexity". In: *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*. IEEE. DOI: 10.1109/ijcnn.2008.4634313.

Jankowski, N. and K. Grąbczewski. (2011). "Universal Meta-Learning Architecture and Algorithms". In: *Studies in Computational Intelligence*. Springer Berlin Heidelberg. 1–76. DOI: 10.1007/978-3-642-20980-2_1.

Jiménez, S., T. D. L. Rosa, S. Fernández, F. Fernández, and D. Borrajo. (2012). "A review of machine learning for automated planning". *The Knowledge Engineering Review*. 27(4): 433–467. DOI: 10.1017/s026988891200001x.

Jin, H., Q. Song, and X. Hu. (2019). "Auto-Keras: An Efficient Neural Architecture Search System". In: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. ACM. DOI: 10.1145/3292500.3330648.

Jones, D. R., M. Schonlau, and W. J. Welch. (1998). "Efficient Global Optimization of Expensive Black-Box Functions". *Journal of Global Optimization*. 13(4): 455–492. DOI: 10.1023/a:1008306431147.

Jouppi, N. P., C. Young, N. Patil, D. Patterson, G. Agrawal, R. Bajwa, S. Bates, S. Bhatia, N. Boden, A. Borchers, R. Boyle, P.-l. Cantin, C. Chao, C. Clark, J. Coriell, M. Daley, M. Dau, J. Dean, B. Gelb, T. V. Ghaemmaghami, R. Gottipati, W. Gulland, R. Hagmann, C. R. Ho, D. Hogberg, J. Hu, R. Hundt, D. Hurt, J. Ibarz, A. Jaffey, A. Jaworski, A. Kaplan, H. Khaitan, D. Killebrew, A. Koch, N. Kumar, S. Lacy, J. Laudon, J. Law, D. Le, C. Leary, Z. Liu, K. Lucke, A. Lundin, G. MacKean, A. Maggiore, M. Mahony, K. Miller, R. Nagarajan, R. Narayanaswami, R. Ni, K. Nix, T. Norrie, M. Omernick, N. Penukonda, A. Phelps, J. Ross, M. Ross, A. Salek, E. Samadiani, C. Severn, G. Sizikov, M. Snelham, J. Souter, D. Steinberg, A. Swing, M. Tan, G. Thorson, B. Tian, H. Toma, E. Tuttle, V. Vasudevan, R. Walter, W. Wang, E. Wilcox, and D. H. Yoon. (2017). "In-Datacenter Performance Analysis of a Tensor Processing Unit". In: *Proceedings of the 44th Annual International Symposium on Computer Architecture*. ACM. DOI: 10.1145/3079856.3080246.

Al-Jubouri, B. (2018). "Multi-criteria optimisation for complex learning prediction systems". *PhD thesis*. Bournemouth University.

Kadane, J. B. and N. A. Lazar. (2004). "Methods and Criteria for Model Selection". *Journal of the American Statistical Association*. 99(465): 279–290. DOI: 10.1198/016214504000000269.

Kadlec, P. and B. Gabrys. (2009a). "Architecture for development of adaptive on-line prediction models". *Memetic Computing*. 1(4): 241–269. DOI: 10.1007/s12293-009-0017-8.

Kadlec, P. and B. Gabrys. (2009b). "Evolving on-line prediction model dealing with industrial data sets". In: *2009 IEEE Workshop on Evolving and Self-Developing Intelligent Systems*. IEEE. DOI: 10.1109/esdis.2009.4938995.

Kadlec, P. and B. Gabrys. (2009c). "Soft Sensor Based on Adaptive Local Learning". In: *Advances in Neuro-Information Processing*. Springer Berlin Heidelberg. 1172–1179. DOI: 10.1007/978-3-642-02490-0_142.

Kadlec, P. and B. Gabrys. (2009d). "Soft sensors: where are we and what are the current and future challenges?" *IFAC Proceedings Volumes*. 42(19): 572–577. DOI: 10.3182/20090921-3-tr-3005.00098.

Kadlec, P. and B. Gabrys. (2010a). "Adaptive on-line prediction soft sensing without historical data". In: *The 2010 International Joint Conference on Neural Networks (IJCNN)*. IEEE. DOI: 10.1109/ijcnn.2010.5596965.

Kadlec, P. and B. Gabrys. (2010b). "Local learning-based adaptive soft sensor for catalyst activation prediction". *AIChE Journal*. 57(5): 1288–1301. DOI: 10.1002/aic.12346.

Kadlec, P., R. Grbić, and B. Gabrys. (2011). "Review of adaptation mechanisms for data-driven soft sensors". *Computers & Chemical Engineering*. 35(1): 1–24. DOI: 10.1016/j.compchemeng.2010.07.034.

Kairouz, P., H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings, R. G. L. D'Oliveira, S. E. Rouayheb, D. Evans, J. Gardner, Z. Garrett, A. Gascón, B. Ghazi, P. B. Gibbons, M. Gruteser, Z. Harchaoui, C. He, L. He, Z. Huo, B. Hutchinson, J. Hsu, M. Jaggi, T. Javidi, G. Joshi, M. Khodak, J. Konečný, A. Korolova, F. Koushanfar, S. Koyejo, T. Lepoint, Y. Liu, P. Mittal, M. Mohri, R. Nock, A. Özgür, R. Pagh, M. Raykova, H. Qi, D. Ramage, R. Raskar, D. Song, W. Song, S. U. Stich, Z. Sun, A. T. Suresh, F. Tramèr, P. Vepakomma, J. Wang, L. Xiong, Z. Xu, Q. Yang, F. X. Yu, H. Yu, and S. Zhao. (2019). "Advances and Open Problems in Federated Learning". *ArXiv*. Dec. arXiv: 1912.04977 [cs.LG].

Kalavri, V. (2016). "Performance optimization techniques and tools for distributed graph processing". *PhD thesis*. KTH Royal Institute of Technology.

Kanter, J. M. and K. Veeramachaneni. (2015). "Deep feature synthesis: Towards automating data science endeavors". In: *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE. DOI: 10.1109/dsaa.2015.7344858.

Kasabov, N. (2001). "Evolving fuzzy neural networks for supervised/unsupervised online knowledge-based learning". *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)*. 31(6): 902–918. DOI: 10.1109/3477.969494.

Katz, G., E. C. R. Shin, and D. Song. (2016). "ExploreKit: Automatic Feature Generation and Selection". In: *2016 IEEE 16th International Conference on Data Mining (ICDM)*. IEEE. DOI: 10.1109/icdm.2016.0123.

Kazakov, V. and F. J. Király. (2019). "Machine Learning Automation Toolbox (MLaut)". *ArXiv*. arXiv: 1901.03678v1 [cs.LG].

Kedziora, D. J., T.-D. Nguyen, K. Musial, and B. Gabrys. (2024). "On taking advantage of opportunistic meta-knowledge to reduce configuration spaces for automated machine learning". *Expert Systems with Applications*. 239: 122359. DOI: 10.1016/j.eswa.2023.122359.

Kerschke, P., H. H. Hoos, F. Neumann, and H. Trautmann. (2019). "Automated Algorithm Selection: Survey and Perspectives". *Evolutionary Computation*. 27(1): 3–45. DOI: 10.1162/evco_a_00242.

Khuat, T. T., F. Chen, and B. Gabrys. (2020). "An improved online learning algorithm for general fuzzy min-max neural network". *ArXiv*. Jan. arXiv: 2001.02391v1 [cs.LG].

Khuat, T. T., D. J. Kedziora, and B. Gabrys. (2023). "The Roles and Modes of Human Interactions with Automated Machine Learning Systems: A Critical Review and Perspectives". *Foundations and Trends® in Human–Computer Interaction*. 17(3-4): 195–387. DOI: 10.1561/1100000091.

Khurana, U., F. Nargesian, H. Samulowitz, E. Khalil, and D. Turaga. (2016a). "Automating feature engineering". *Transformation*. 10(10): 10.

Khurana, U., H. Samulowitz, and D. Turaga. (2017). "Feature Engineering for Predictive Modeling using Reinforcement Learning". *ArXiv*. arXiv: 1709.07150v1 [cs.AI].

Khurana, U., D. Turaga, H. Samulowitz, and S. Parthasrathy. (2016b). "Cognito: Automated Feature Engineering for Supervised Learning". In: *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*. IEEE. DOI: 10.1109/icdmw.2016.0190.

Kietz, J.-U., F. Serban, A. Bernstein, and S. Fischer. (2009). "Towards cooperative planning of data mining workflows". In: *Proc of the ECML/PKDD09 Workshop on Third Generation Data Mining: Towards Service-oriented Knowledge Discovery (SoKD-09)*. DOI: 10.5167/uzh-25868.

Kietz, J.-U., F. Serban, A. Bernstein, and S. Fischer. (2012). "Designing KDD-Workflows via HTN-Planning for Intelligent Discovery Assistance". In: *Planning to Learn 2012, Workshop at ECAI 2012*. Ed. by J. Vanschoren, J.-U. Kietz, and P. Brazdil. CEUR Workshop Proceedings. DOI: 10.5167/uzh-67514.

Kim, J., J. Jeong, and S. Choi. (2016). "AutoML Challenge: AutoML Framework Using Random Space Partitioning Optimizer". In: *Workshop on Automated Machine Learning (AutoML), ICML*. 1–4.

Kim, Y., Y. Li, H. Park, Y. Venkatesha, and P. Panda. (2022). "Neural Architecture Search for Spiking Neural Networks". In: *Lecture Notes in Computer Science*. Springer Nature Switzerland. 36–56. DOI: 10.1007/978-3-031-20053-3_3.

Klau, D., M. Zöller, and C. Tutschku. (2023). "Bringing Quantum Algorithms to Automated Machine Learning: A Systematic Review of AutoML Frameworks Regarding Extensibility for QML Algorithms". *ArXiv*. DOI: 10.48550/ARXIV.2310.04238.

Klein, A., S. Falkner, S. Bartels, P. Hennig, and F. Hutter. (2017). "Fast Bayesian Optimization of Machine Learning Hyperparameters on Large Datasets". In: *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*. Ed. by A. Singh and J. Zhu. Vol. 54. *Proceedings of Machine Learning Research*. Fort Lauderdale, FL, USA: PMLR. 528–536. URL: http://proceedings.mlr.press/v54/klein17a.html.

Kohavi, R. and G. H. John. (1997). "Wrappers for feature subset selection". *Artificial Intelligence*. 97(1-2): 273–324. DOI: 10.1016/s0004-3702(97)00043-x.

Kolter, J. Z. and M. A. Maloof. (2007). "Dynamic weighted majority: An ensemble method for drifting concepts". *Journal of Machine Learning Research*. 8(Dec): 2755–2790.

Komer, B., J. Bergstra, and C. Eliasmith. (2014). "Hyperopt-Sklearn: Automatic Hyperparameter Configuration for Scikit-Learn". In: *Proceedings of the 13th Python in Science Conference*. SciPy. DOI: 10.25080/majora-14bd3278-006.

Komer, B., J. Bergstra, and C. Eliasmith. (2019). "Hyperopt-Sklearn". In: *Automated Machine Learning*. Springer International Publishing. 97–111. DOI: 10.1007/978-3-030-05318-5_5.

Kordík, P., J. Černý, and T. Frýda. (2017). "Discovering predictive ensembles for transfer learning and meta-learning". *Machine Learning*. 107(1): 177–207. DOI: 10.1007/s10994-017-5682-0.

Kotthoff, L., C. Thornton, H. H. Hoos, F. Hutter, and K. Leyton-Brown. (2019). "Auto-WEKA: Automatic Model Selection and Hyperparameter Optimization in WEKA". In: *Automated Machine Learning*. Springer International Publishing. 81–95. DOI: 10.1007/978-3-030-05318-5_4.

Koza, J. (1990). "Genetically breeding populations of computer programs to solve problems in artificial intelligence". In: *[1990] Proceedings of the 2nd International IEEE Conference on Tools for Artificial Intelligence*. IEEE Comput. Soc. Press. DOI: 10.1109/tai.1990.130444.

Kraska, T. (2018). "Northstar: an interactive data science system". *Proceedings of the VLDB Endowment*. 11(12): 2150–2164. DOI: 10.14778/3229863.3240493.

Kraska, T., A. Talwalkar, J. C. Duchi, R. Griffith, M. J. Franklin, and M. I. Jordan. (2013). "MLbase: A Distributed Machine-learning System." In: *CIDR*. Vol. 1. 2–1.

Krizhevsky, A., I. Sutskever, and G. E. Hinton. (2012). "ImageNet Classification with Deep Convolutional Neural Networks". In: *Advances in Neural Information Processing Systems 25*. Ed. by F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger. Curran Associates, Inc. 1097–1105. DOI: 10.1145/3065386.

Kurgan, L. A. and P. Musilek. (2006). "A survey of Knowledge Discovery and Data Mining process models". *The Knowledge Engineering Review*. 21(1): 1–24. DOI: 10.1017/s0269888906000737.

Kushner, H. J. (1964). "A New Method of Locating the Maximum Point of an Arbitrary Multipeak Curve in the Presence of Noise". *Journal of Basic Engineering*. 86(1): 97–106. DOI: 10.1115/1.3653121.

Lacoste, A., H. Larochelle, M. Marchand, and F. Laviolette. (2014). "Sequential Model-Based Ensemble Optimization". In: *Proceedings of the Thirtieth Conference on Uncertainty in Artificial Intelligence. UAI'14*. Quebec City, Quebec, Canada: AUAI Press. 440–448.

Lam, H. T., T. N. Minh, M. Sinn, B. Buesser, and M. Wistuba. (2018). "Neural Feature Learning From Relational Database". *ArXiv*. arXiv: 1801.05372v4 [cs.AI].

Lam, H. T., J.-M. Thiebaut, M. Sinn, B. Chen, T. Mai, and O. Alkan. (2017). "One button machine for automating feature engineering in relational databases". *ArXiv*. arXiv: 1706.00327v1 [cs.DB].

Leather, H., E. Bonilla, and M. O'Boyle. (2009). "Automatic Feature Generation for Machine Learning Based Optimizing Compilation". In: *2009 International Symposium on Code Generation and Optimization*. IEEE. DOI: 10.1109/cgo.2009.21.

Lee, D. J.-L., S. Macke, D. Xin, A. Lee, S. Huang, and A. Parameswaran. (2019). "A Human-in-the-loop Perspective on AutoML: Milestones and the Road Ahead". *IEEE Data Eng. Bull.* 42(2): 59–70.

Leite, R. and P. Brazdil. (2005). "Predicting relative performance of classifiers from samples". In: *Proceedings of the 22nd international conference on Machine learning - ICML '05*. ACM Press. DOI: 10.1145/1102351.1102414.

Leite, R. and P. Brazdil. (2010). "Active Testing Strategy to Predict the Best Classification Algorithm via Sampling and Metalearning". In: *Proceedings of the 2010 Conference on ECAI 2010: 19th European Conference on Artificial Intelligence*. NLD: IOS Press. 309–314.

Leite, R., P. Brazdil, and J. Vanschoren. (2012). "Selecting Classification Algorithms with Active Testing". In: *Machine Learning and Data Mining in Pattern Recognition*. Springer Berlin Heidelberg. 117–131. DOI: 10.1007/978-3-642-31537-4_10.

Lemke, C., M. Budka, and B. Gabrys. (2015). "Metalearning: a survey of trends and technologies". *Artificial Intelligence Review*. 44(1): 117–130. DOI: 10.1007/s10462-013-9406-y.

Lemke, C. and B. Gabrys. (2008). "Do We Need Experts for Time Series Forecasting?" In: *16th European Symposium on ArtiProceedings of the ficial Neural Networks (ESANN'2008)*. d-side. 253–258. URL: http://eprints.bournemouth.ac.uk/8516/.

Lemke, C. and B. Gabrys. (2010a). "Meta-learning for time series forecasting and forecast combination". *Neurocomputing*. 73(10-12): 2006–2016. DOI: 10.1016/j.neucom.2009.09.020.

Lemke, C. and B. Gabrys. (2010b). "Meta-learning for time series forecasting in the NN GC1 competition". In: *International Conference on Fuzzy Systems*. IEEE. DOI: 10.1109/fuzzy.2010.5584001.

Lemke, C., S. Riedel, and B. Gabrys. (2012). "Evolving forecast combination structures for airline revenue management". *Journal of Revenue and Pricing Management*. 12(3): 221–234. DOI: 10.1057/rpm.2012.30.

Lévesque, J.-C., C. Gagné, and R. Sabourin. (2016). "Bayesian Hyperparameter Optimization for Ensemble Learning". In: *Proceedings of the Thirty-Second Conference on Uncertainty in Artificial Intelligence. UAI'16*. Jersey City, New Jersey, USA: AUAI Press. 437–446.

Li, Y.-F., H. Wang, T. Wei, and W.-W. Tu. (2019). "Towards Automated Semi-Supervised Learning". *Proceedings of the AAAI Conference on Artificial Intelligence*. 33: 4237–4244. DOI: 10.1609/aaai.v33i01.33014237.

Li, K. and J. Malik. (2016). "Learning to Optimize". *ArXiv*. arXiv: 1606.01885v1 [cs.LG].

Li, L. and A. Talwalkar. (2019). "Random Search and Reproducibility for Neural Architecture Search". In: *Proceedings of the Thirty-Fifth Conference on Uncertainty in Artificial Intelligence, UAI 2019, Tel Aviv, Israel, July 22-25, 2019*. Ed. by A. Globerson and R. Silva. AUAI Press. 129. URL: http://auai.org/uai2019/proceedings/papers/129.pdf.

Li, L., K. Jamieson, G. DeSalvo, A. Rostamizadeh, and A. Talwalkar. (2018). "Hyperband: A Novel Bandit-Based Approach to Hyperparameter Optimization". *Journal of Machine Learning Research*. 18(185): 1–52. URL: http://jmlr.org/papers/v18/16-558.html.

Li, Y., Y. Shen, W. Zhang, C. Zhang, and B. Cui. (2022). "VolcanoML: speeding up end-to-end AutoML via scalable search space decomposition". *The VLDB Journal*. 32(2): 389–413. DOI: 10.1007/s00778-022-00752-2.

Lindauer, M., K. Eggensperger, M. Feurer, A. Biedenkapp, D. Deng, C. Benjamins, T. Ruhkopf, R. Sass, and F. Hutter. (2022). "SMAC3: A Versatile Bayesian Optimization Package for Hyperparameter Optimization". *J. Mach. Learn. Res.* 23(1).

Liu, B. (2018). "A Very Brief and Critical Discussion on AutoML". *ArXiv*. Nov. arXiv: 1811.03822v1 [cs.AI].

Liu, H., K. Simonyan, and Y. Yang. (2019a). "DARTS: Differentiable Architecture Search". In: *International Conference on Learning Representations*. URL: https://openreview.net/forum?id=S1eYHoC5FX.

Liu, S., P. Ram, D. Vijaykeerthy, D. Bouneffouf, G. Bramble, H. Samulowitz, D. Wang, A. Conn, and A. Gray. (2020). "An ADMM Based Framework for AutoML Pipeline Configuration". *Proceedings of the AAAI Conference on Artificial Intelligence*. 34(04): 4892–4899. DOI: 10.1609/aaai.v34i04.5926.

Liu, Z., I. Guyon, J. J. Junior, M. Madadi, S. Escalera, A. Pavao, H. J. Escalante, W.-W. Tu, Z. Xu, and S. Treguer. (2019b). "AutoCV Challenge Design and Baseline Results". In: *CAp 2019 - Conférence sur l'Apprentissage Automatique*. Toulouse, France. URL: https://hal.archives-ouvertes.fr/hal-02265053.

Lorena, A. C., A. I. Maciel, P. B. C. de Miranda, I. G. Costa, and R. B. C. Prudêncio. (2017). "Data complexity meta-features for regression problems". *Machine Learning*. 107(1): 209–246. DOI: 10.1007/s10994-017-5681-1.

Lorraine, J., P. Vicol, and D. Duvenaud. (2020). "Optimizing Millions of Hyperparameters by Implicit Differentiation". In: *Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics*. Ed. by S. Chiappa and R. Calandra. Vol. 108. *Proceedings of Machine Learning Research*. PMLR. 1540–1552. URL: https://proceedings.mlr.press/v108/lorraine20a.html.

Lu, Z., H. Pu, F. Wang, Z. Hu, and L. Wang. (2017). "The Expressive Power of Neural Networks: A View from the Width". In: *Advances in Neural Information Processing Systems 30*. Ed. by I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett. Curran Associates, Inc. 6231–6239. URL: http://papers.nips.cc/paper/7203-the-expressive-power-of-neural-networks-a-view-from-the-width.pdf.

Luo, G. (2016a). "A review of automatic selection methods for machine learning algorithms and hyper-parameter values". *Network Modeling Analysis in Health Informatics and Bioinformatics*. 5(1). DOI: 10.1007/s13721-016-0125-6.

Luo, G. (2016b). “PredicT-ML: a tool for automating machine learning model building with big clinical data”. *Health Information Science and Systems*. 4(1). DOI: 10.1186/s13755-016-0018-1.

MacKay, D. J. C. (1992). “A Practical Bayesian Framework for Backpropagation Networks”. *Neural Computation*. 4(3): 448–472. DOI: 10.1162/neco.1992.4.3.448.

Madrid, J. G., H. J. Escalante, E. F. Morales, W.-W. Tu, Y. Yu, L. Sun-Hosoya, I. Guyon, and M. Sebag. (2019). “Towards AutoML in the presence of Drift: first results”. *ArXiv*. July. arXiv: 1907.10772v1 [cs.LG].

Madrigal, F., C. Maurice, and F. Lerasle. (2018). “Hyper-parameter optimization tools comparison for multiple object tracking applications”. *Machine Vision and Applications*. 30(2): 269–289. DOI: 10.1007/s00138-018-0984-1.

Malone, B., K. Kangas, M. Jarvisalo, M. Koivisto, and P. Myllymaki. (2014). “Predicting the Hardness of Learning Bayesian Networks”. *Proceedings of the AAAI Conference on Artificial Intelligence*. 28(1). URL: https://ojs.aaai.org/index.php/AAAI/article/view/9075.

Malone, B., K. Kangas, M. Järvisalo, M. Koivisto, and P. Myllymäki. (2017a). “AS-ASL: Algorithm Selection with Auto-sklearn”. In: *Proceedings of the Open Algorithm Selection Challenge*. Ed. by M. Lindauer, J. N. van Rijn, and L. Kotthoff. Vol. 79. *Proceedings of Machine Learning Research*. Brussels, Belgium: PMLR. 19–22. URL: http://proceedings.mlr.press/v79/malone17a.html.

Malone, B., K. Kangas, M. Järvisalo, M. Koivisto, and P. Myllymäki. (2017b). “Empirical hardness of finding optimal Bayesian network structures: algorithm selection and runtime prediction”. *Machine Learning*. 107(1): 247–283. DOI: 10.1007/s10994-017-5680-2.

Markovitch, S. and D. Rosenstein. (2002). “Feature Generation Using General Constructor Functions”. *Machine Learning*. 49(1): 59–98. DOI: 10.1023/a:1014046307775.

Maron, O. and A. W. Moore. (1994). “Hoeffding Races: Accelerating Model Selection Search for Classification and Function Approximation”. In: *Proceedings of the 6th International Conference on Neural Information Processing Systems. NIPS’93*. Denver, Colorado: Morgan Kaufmann Publishers Inc. 59–66.

Matheus, C. J. and L. A. Rendell. (1989). "Constructive Induction On Decision Trees". In: *IJCAI*. Vol. 89. 645–650.

McCloskey, M. and N. J. Cohen. (1989). "Catastrophic Interference in Connectionist Networks: The Sequential Learning Problem". In: *Psychology of Learning and Motivation*. Elsevier. 109–165. DOI: 10.1016/s0079-7421(08)60536-8.

McConachie, D. and D. Berenson. (2020). "Bandit-Based Model Selection for Deformable Object Manipulation". In: *Springer Proceedings in Advanced Robotics*. Springer International Publishing. 704–719. DOI: 10.1007/978-3-030-43089-4_45.

Mendoza, H., A. Klein, M. Feurer, J. T. Springenberg, and F. Hutter. (2016). "Towards Automatically-Tuned Neural Networks". In: *Proceedings of the Workshop on Automatic Machine Learning*. Ed. by F. Hutter, L. Kotthoff, and J. Vanschoren. Vol. 64. *Proceedings of Machine Learning Research*. New York, New York, USA: PMLR. 58–65. URL: http://proceedings.mlr.press/v64/mendoza_towards_2016.html.

Mendoza, H., A. Klein, M. Feurer, J. T. Springenberg, M. Urban, M. Burkart, M. Dippel, M. Lindauer, and F. Hutter. (2019). "Towards Automatically-Tuned Deep Neural Networks". In: *Automated Machine Learning*. Springer International Publishing. 135–149. DOI: 10.1007/978-3-030-05318-5_7.

Meta-learning and Algorithm Selection Workshop at ECAI 2014. (2014). Ed. by J. Vanschoren, P. Brazdil, C. Soares, and L. Kotthoff.

Michalski, R. S. (1986). *Understanding the nature of learning: Issues and research directions*. Morgan Kaufmann Publishers.

Milutinovic, M., A. G. Baydin, R. Zinkov, W. Harvey, D. Song, F. Wood, and W. Shen. (2017). "End-to-end training of differentiable pipelines across machine learning frameworks". *NeurIPS Workshop*.

Močkus, J. (1975). "On bayesian methods for seeking the extremum". In: *Optimization Techniques IFIP Technical Conference Novosibirsk, July 1–7, 1974*. Springer Berlin Heidelberg. 400–404. DOI: 10.1007/3-540-07165-2_55.

Mohr, F., M. Wever, E. Hullermeier, and A. Faez. (2018a). "Towards the Automated Composition of Machine Learning Services". In: *2018 IEEE International Conference on Services Computing (SCC)*. IEEE. DOI: 10.1109/scc.2018.00039.

Mohr, F., M. Wever, and E. Hüllermeier. (2018b). "Automated Machine Learning Service Composition". *ArXiv*. arXiv: 1809.00486v1 [cs.SE].

Mohr, F., M. Wever, and E. Hüllermeier. (2018c). "ML-Plan: Automated machine learning via hierarchical planning". *Machine Learning*. 107(8-10): 1495–1515. DOI: 10.1007/s10994-018-5735-z.

Muñoz, M. A., L. Villanova, D. Baatar, and K. Smith-Miles. (2017). "Instance spaces for machine learning classification". *Machine Learning*. 107(1): 109–147. DOI: 10.1007/s10994-017-5629-5.

Nakhaeizadeh, G. and A. Schnabl. (1997). "Development of Multi-Criteria Metrics for Evaluation of Data Mining Algorithms". In: *KDD*. 37–42.

Nargesian, F., H. Samulowitz, U. Khurana, E. B. Khalil, and D. Turaga. (2017). "Learning Feature Engineering for Classification". In: *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence*. International Joint Conferences on Artificial Intelligence Organization. DOI: 10.24963/ijcai.2017/352.

Neal, B., S. Mittal, A. Baratin, V. Tantia, M. Scicluna, S. Lacoste-Julien, and I. Mitliagkas. (2018). "A Modern Take on the Bias-Variance Tradeoff in Neural Networks". *ArXiv*. Oct. arXiv: 1810.08591 [cs.LG].

Nguyen, P., M. Hilario, and A. Kalousis. (2014). "Using Meta-mining to Support Data Mining Workflow Planning and Optimization". *Journal of Artificial Intelligence Research*. 51: 605–644. DOI: 10.1613/jair.4377.

Nguyen, T.-D., B. Gabrys, and K. Musial. (2020a). "AutoWeka4MCPS-AVATAR: Accelerating Automated Machine Learning Pipeline Composition and Optimisation". *ArXiv*. Nov. arXiv: 2011.11846v1 [cs.LG].

Nguyen, T.-D., D. J. Kedziora, K. Musial, and B. Gabrys. (2021). "Exploring Opportunistic Meta-knowledge to Reduce Search Spaces for Automated Machine Learning". *International Joint Conference on Neural Network 2021*. arXiv: 2105.00282 [cs.LG].

Nguyen, T.-D., T. Maszczyk, K. Musial, M.-A. Zöller, and B. Gabrys. (2020b). "AVATAR - Machine Learning Pipeline Evaluation Using Surrogate Model". In: *Lecture Notes in Computer Science*. Springer International Publishing. 352–365. DOI: 10.1007/978-3-030-44584-3_28.

Nisioti, E., K. Chatzidimitriou, and A. Symeonidis. (2018). "Predicting hyperparameters from meta-features in binary classification problems". In: *AutoML Workshop at ICML*.

Nural, M. V., H. Peng, and J. A. Miller. (2017). "Using meta-learning for model type selection in predictive big data analytics". In: *2017 IEEE International Conference on Big Data (Big Data)*. IEEE. DOI: 10.1109/bigdata.2017.8258149.

Olson, R. S., N. Bartley, R. J. Urbanowicz, and J. H. Moore. (2016a). "Evaluation of a Tree-based Pipeline Optimization Tool for Automating Data Science". In: *Proceedings of the 2016 on Genetic and Evolutionary Computation Conference - GECCO '16*. ACM Press. DOI: 10.1145/2908812.2908918.

Olson, R. S., R. J. Urbanowicz, P. C. Andrews, N. A. Lavender, L. C. Kidd, and J. H. Moore. (2016b). "Automating Biomedical Data Science Through Tree-Based Pipeline Optimization". In: *Applications of Evolutionary Computation*. Springer International Publishing. 123–137. DOI: 10.1007/978-3-319-31204-0_9.

Orabona, F. (2014). "Simultaneous Model Selection and Optimization through Parameter-free Stochastic Learning". In: *Advances in Neural Information Processing Systems 27*. Ed. by Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger. Curran Associates, Inc. 1116–1124. URL: http://papers.nips.cc/paper/5503-simultaneous-model-selection-and-optimization-through-parameter-free-stochastic-learning.pdf.

Orabona, F. and D. Pál. (2016). "Coin Betting and Parameter-Free Online Learning". *ArXiv*. arXiv: 1602.04128 [cs.LG].

Orabona, F. and T. Tommasi. (2017). "Training Deep Networks without Learning Rates Through Coin Betting". In: *Advances in Neural Information Processing Systems*. Ed. by I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett. Vol. 30. Curran Associates, Inc. URL: https://proceedings.neurips.cc/paper/2017/file/7c82fab8c8f89124e2ce92984e04fb40-Paper.pdf.

Page, E. S. (1954). "Continuous Inspection Schemes". *Biometrika*. 41(1/2): 100. DOI: 10.2307/2333009.

Pan, S. J. and Q. Yang. (2010). "A Survey on Transfer Learning". *IEEE Transactions on Knowledge and Data Engineering*. 22(10): 1345–1359. DOI: 10.1109/tkde.2009.191.

Parmezan, A. R. S., H. D. Lee, N. Spolaôr, and F. C. Wu. (2021). "Automatic recommendation of feature selection algorithms based on dataset characteristics". *Expert Systems with Applications*. 185: 115589. DOI: 10.1016/j.eswa.2021.115589.

Parmezan, A. R. S., H. D. Lee, and F. C. Wu. (2017). "Metalearning for choosing feature selection algorithms in data mining: Proposal of a new framework". *Expert Systems with Applications*. 75: 1–24. DOI: 10.1016/j.eswa.2017.01.013.

Patterson, D., J. Gonzalez, Q. Le, C. Liang, L.-M. Munguia, D. Rothchild, D. So, M. Texier, and J. Dean. (2021). "Carbon Emissions and Large Neural Network Training". *ArXiv*. arXiv: 2104.10350 [cs.LG].

Pazzani, M. J. (1998). "Constructive Induction of Cartesian Product Attributes". In: *Feature Extraction, Construction and Selection*. Springer US. 341–354. DOI: 10.1007/978-1-4615-5725-8_21.

Peng, D., X. Dong, E. Real, M. Tan, Y. Lu, H. Liu, G. Bender, A. Kraft, C. Liang, and Q. V. Le. (2021). "PyGlove: Symbolic Programming for Automated Machine Learning". *ArXiv*. arXiv: 2101.08809 [cs.LG].

Peng, R. D. (2011). "Reproducible Research in Computational Science". *Science*. 334(6060): 1226–1227. DOI: 10.1126/science.1213847.

Petrak, J. (2000). "Fast subsampling performance estimates for classification algorithm selection". In: *Proceedings of the ECML-00 Workshop on Meta-Learning: Building Automatic Advice Strategies for Model Selection and Method Combination*. 3–14.

Pfahringer, B., H. Bensusan, and C. G. Giraud-Carrier. (2000). "Meta-Learning by Landmarking Various Learning Algorithms". In: *ICML*. 743–750.

Pham, H., M. Guan, B. Zoph, Q. Le, and J. Dean. (2018). "Efficient Neural Architecture Search via Parameters Sharing". In: *Proceedings of the 35th International Conference on Machine Learning*. Ed. by J. Dy and A. Krause. Vol. 80. *Proceedings of Machine Learning Research*. PMLR. 4095–4104. URL: https://proceedings.mlr.press/v80/pham18a.html.

Pokrajac, D., A. Lazarevic, and L. J. Latecki. (2007). "Incremental Local Outlier Detection for Data Streams". In: *2007 IEEE Symposium on Computational Intelligence and Data Mining*. IEEE. DOI: 10.1109/cidm.2007.368917.

Preuveneers, D. (2023). "AutoFL: Towards AutoML in a Federated Learning Context". *Applied Sciences*. 13(14): 8019. DOI: 10.3390/app13148019.

Probst, P., A.-L. Boulesteix, and B. Bischl. (2019a). "Tunability: Importance of Hyperparameters of Machine Learning Algorithms". *Journal of Machine Learning Research*. 20(53): 1–32. URL: http://jmlr.org/papers/v20/18-444.html.

Probst, P., M. N. Wright, and A.-L. Boulesteix. (2019b). "Hyperparameters and tuning strategies for random forest". *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*. 9(3). DOI: 10.1002/widm.1301.

Purucker, L. and J. Beel. (2023). "Assembled-OpenML: Creating Efficient Benchmarks for Ensembles in AutoML with OpenML". *ArXiv*. DOI: 10.48550/ARXIV.2307.00285.

Qu, Y., X. Chen, Y. Zhao, and X. Ju. (2018). "Impact of Hyper Parameter Optimization for Cross-Project Software Defect Prediction". *International Journal of Performability Engineering*. 14(6), 1291: 1291. DOI: 10.23940/ijpe.18.06.p20.12911299.

Raina, R., A. Battle, H. Lee, B. Packer, and A. Y. Ng. (2007). "Self-taught learning: Transfer Learning from Unlabeled Data". In: *Proceedings of the 24th international conference on Machine learning - ICML '07*. ACM Press. DOI: 10.1145/1273496.1273592.

Rakotoarison, H., L. Milijaona, A. Rasoanaivo, M. Sebag, and M. Schoenauer. (2022). "Learning Meta-features for AutoML". In: *ICLR 2022 - International Conference on Learning Representations (spotlight)*. Virtual, United States. URL: https://inria.hal.science/hal-03583789.

Real, E., A. Aggarwal, Y. Huang, and Q. V. Le. (2019). "Regularized Evolution for Image Classifier Architecture Search". *Proceedings of the AAAI Conference on Artificial Intelligence*. 33: 4780–4789. DOI: 10.1609/aaai.v33i01.33014780.

Real, E., C. Liang, D. So, and Q. Le. (2020). "AutoML-Zero: Evolving Machine Learning Algorithms From Scratch". In: *Proceedings of the 37th International Conference on Machine Learning*. Ed. by H. D. III and A. Singh. Vol. 119. *Proceedings of Machine Learning Research*. Virtual: PMLR. 8007–8019. URL: http://proceedings.mlr.press/v119/real20a.html.

Real, E., S. Moore, A. Selle, S. Saxena, Y. L. Suematsu, J. Tan, Q. V. Le, and A. Kurakin. (2017). "Large-Scale Evolution of Image Classifiers". In: *Proceedings of the 34th International Conference on Machine Learning - Volume 70*. *ICML'17*. Sydney, NSW, Australia: JMLR.org. 2902–2911.

Reif, M., F. Shafait, and A. Dengel. (2012). "Meta-learning for evolutionary parameter optimization of classifiers". *Machine Learning*. 87(3): 357–380. DOI: 10.1007/s10994-012-5286-7.

Ren, P., Y. Xiao, X. Chang, P.-Y. Huang, Z. Li, X. Chen, and X. Wang. (2020). "A Comprehensive Survey of Neural Architecture Search: Challenges and Solutions". *ArXiv*. June. arXiv: 2006.02903v1 [cs.LG].

Rice, J. R. (1976). "The Algorithm Selection Problem". In: *Advances in Computers*. Elsevier. 65–118. DOI: 10.1016/s0065-2458(08)60520-3.

Riedel, S. and B. Gabrys. (2009). "Pooling for Combination of Multilevel Forecasts". *IEEE Transactions on Knowledge and Data Engineering*. 21(12): 1753–1766. DOI: 10.1109/tkde.2009.18.

Riedel, S. and B. Gabrys. (2005). "Hierarchical Multilevel Approaches of Forecast Combination". In: *Operations Research Proceedings 2004*. Springer Berlin Heidelberg. 479–486. DOI: 10.1007/3-540-27679-3_59.

Riedel, S. and B. Gabrys. (2007a). "Combination of Multi Level Forecasts". *The Journal of VLSI Signal Processing Systems for Signal, Image, and Video Technology*. 49(2): 265–280. DOI: 10.1007/s11265-007-0076-3.

Riedel, S. and B. Gabrys. (2007b). "Dynamic Pooling for the Combination of Forecasts generated using Multi Level Learning". In: *2007 International Joint Conference on Neural Networks*. IEEE. DOI: 10.1109/ijcnn.2007.4370999.

Riera-Fernandez, P., C. R. Munteanu, N. Pedreira-Souto, R. Martín-Romalde, A. Duardo-Sanchez, and H. Gonzalez-Diaz. (2011). "Definition of Markov-Harary Invariants and Review of Classic Topological Indices and Databases in Biology, Parasitology, Technology, and Social-Legal Networks". *Current Bioinformatics*. 6(1): 94–121. DOI: 10.2174/157489311795222338.

Rijn, J. N. van, S. M. Abdulrahman, P. Brazdil, and J. Vanschoren. (2015a). "Fast Algorithm Selection Using Learning Curves". In: *Advances in Intelligent Data Analysis XIV*. Springer International Publishing. 298–309. DOI: 10.1007/978-3-319-24465-5_26.

Rijn, J. N. van, G. Holmes, B. Pfahringer, and J. Vanschoren. (2015b). "Having a Blast: Meta-Learning and Heterogeneous Ensembles for Data Streams". In: *2015 IEEE International Conference on Data Mining*. IEEE. DOI: 10.1109/icdm.2015.55.

Rijn, J. N. van, G. Holmes, B. Pfahringer, and J. Vanschoren. (2017). "The online performance estimation framework: heterogeneous ensemble learning for data streams". *Machine Learning*. 107(1): 149–176. DOI: 10.1007/s10994-017-5686-9.

Rijn, J. N. van and F. Hutter. (2018). "Hyperparameter Importance Across Datasets". In: *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. ACM. DOI: 10.1145/3219819.3220058.

Rittho, O., R. Klinkenberg, S. Fischer, I. Mierswa, and S. Felske. (2001). "Yale: Yet another learning environment". In: *LLWA 01-Tagungsband der GI-Workshop-Woche Lernen-Lehren-Wissen-Adaptivität*. No. 763. Citeseer. 84–92.

Rivolli, A., L. P. Garcia, C. Soares, J. Vanschoren, and A. C. de Carvalho. (2022). "Meta-features for meta-learning". *Knowledge-Based Systems*. 240: 108101. DOI: 10.1016/j.knosys.2021.108101.

Roschewitz, D., K. Driessens, and P. Collins. (2018). "Simultaneous Ensemble Generation and Hyperparameter Optimization for Regression". In: *Communications in Computer and Information Science*. Springer International Publishing. 116–130. DOI: 10.1007/978-3-319-76892-2_9.

Rudin, C. (2019). "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead". *Nature Machine Intelligence*. 1(5): 206–215. DOI: 10.1038/s42256-019-0048-x.

Runge, F., D. Stoll, S. Falkner, and F. Hutter. (2019). "Learning to Design RNA". In: *International Conference on Learning Representations*. URL: https://openreview.net/forum?id=ByfyHh05tQ.

Ruta, D. and B. Gabrys. (2002). "A Theoretical Analysis of the Limits of Majority Voting Errors for Multiple Classifier Systems". *Pattern Analysis and Applications*. 5(4): 333–350. DOI: 10.1007/s100440200030.

Ruta, D. and B. Gabrys. (2003). "Set Analysis of Coincident Errors and Its Applications for Combining Classifiers". In: *Pattern Recognition and String Matching*. Springer US. 647–671. DOI: 10.1007/978-1-4613-0231-5_25.

Ruta, D. and B. Gabrys. (2005). "Classifier selection for majority voting". *Information Fusion*. 6(1): 63–81. DOI: 10.1016/j.inffus.2004.04.008.

Ruta, D., B. Gabrys, and C. Lemke. (2011). "A Generic Multilevel Architecture for Time Series Prediction". *IEEE Transactions on Knowledge and Data Engineering*. 23(3): 350–359. DOI: 10.1109/tkde.2010.137.

Sá, A. G. C. de, W. J. G. S. Pinto, L. O. V. B. Oliveira, and G. L. Pappa. (2017). "RECIPE: A Grammar-Based Framework for Automatically Evolving Classification Pipelines". In: *Lecture Notes in Computer Science*. Springer International Publishing. 246–261. DOI: 10.1007/978-3-319-55696-3_16.

Salvador, M. M. (2017). "Automatic and adaptive preprocessing for the development of predictive models." *PhD thesis*. Bournemouth University.

Salvador, M. M., M. Budka, and B. Gabrys. (2016a). "Adapting multicomponent predictive systems using hybrid adaptation strategies with auto-weka in process industry". In: *Workshop on Automatic Machine Learning*. 48–57.

Salvador, M. M., M. Budka, and B. Gabrys. (2016b). "Effects of Change Propagation Resulting from Adaptive Preprocessing in Multicomponent Predictive Systems". *Procedia Computer Science*. 96: 713–722. DOI: 10.1016/j.procs.2016.08.255.

Salvador, M. M., M. Budka, and B. Gabrys. (2016c). "Towards Automatic Composition of Multicomponent Predictive Systems". In: *Lecture Notes in Computer Science*. Springer International Publishing. 27–39. DOI: 10.1007/978-3-319-32034-2_3.

Salvador, M. M., M. Budka, and B. Gabrys. (2017). "Modelling Multi-Component Predictive Systems as Petri Nets". In: *15th Annual Industrial Simulation Conference*. Ed. by J. Kacprzyk and J. Owsinski. Eurosis-ETI. 17–23. URL: http://eprints.bournemouth.ac.uk/30605/.

Salvador, M. M., M. Budka, and B. Gabrys. (2019). "Automatic Composition and Optimization of Multicomponent Predictive Systems With an Extended Auto-WEKA". *IEEE Transactions on Automation Science and Engineering*. 16(2): 946–959. DOI: 10.1109/tase.2018.2876430.

Samuel, A. L. (1959). "Some Studies in Machine Learning Using the Game of Checkers". *IBM Journal of Research and Development*. 3(3): 210–229. DOI: 10.1147/rd.33.0210.

Samuel, A. L. (1960). "Some Moral and Technical Consequences of Automation–A Refutation". *Science*. 132(3429): 741–742. DOI: 10.1126/science.132.3429.741.

Schaer, R., H. Müller, and A. Depeursinge. (2016). "Optimized Distributed Hyperparameter Search and Simulation for Lung Texture Classification in CT Using Hadoop". *Journal of Imaging*. 2(2): 19. DOI: 10.3390/jimaging2020019.

Schoenfeld, B., C. Giraud-Carrier, M. Poggemann, J. Christensen, and K. Seppi. (2018). "Preprocessor Selection for Machine Learning Pipelines". *ArXiv*. arXiv: 1810.09942v1 [cs.LG].

Schuchmann, S. (2019). "Analyzing the Prospect of an Approaching AI Winter". en. *MA thesis*. DOI: 10.13140/RG.2.2.10932.91524.

Scott, S. L. (2010). "A modern Bayesian look at the multi-armed bandit". *Applied Stochastic Models in Business and Industry*. 26(6): 639–658. DOI: 10.1002/asmb.874.

Scriven, A., D. J. Kedziora, K. Musial, and B. Gabrys. (2022). "The Technological Emergence of AutoML: A Survey of Performant Software and Applications in the Context of Industry". *ArXiv*. DOI: 10.48550/ARXIV.2211.04148.

Sculley, D., G. Holt, D. Golovin, E. Davydov, T. Phillips, D. Ebner, V. Chaudhary, M. Young, J.-F. Crespo, and D. Dennison. (2015). "Hidden Technical Debt in Machine Learning Systems". In: *Advances in Neural Information Processing Systems 28*. Ed. by C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett. Curran Associates, Inc. 2503–2511. URL: http://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf.

Sehnke, F., M. D. Felder, and A. K. Kaifel. (2012). "Learn-o-matic: A fully automated machine learning suite for profile retrieval applications". In: *Proceedings of the 2012 EUMETSAT Meteorological Satellite Conference*.

Sehnke, F., C. Osendorfer, T. Rückstieß, A. Graves, J. Peters, and J. Schmidhuber. (2010). "Parameter-exploring policy gradients". *Neural Networks*. 23(4): 551–559. DOI: 10.1016/j.neunet.2009.12.004.

Serban, F., J. Vanschoren, J.-U. Kietz, and A. Bernstein. (2013). "A survey of intelligent assistants for data analysis". *ACM Computing Surveys*. 45(3): 1–35. DOI: 10.1145/2480741.2480748.

Shahriari, B., K. Swersky, Z. Wang, R. P. Adams, and N. de Freitas. (2016). "Taking the Human Out of the Loop: A Review of Bayesian Optimization". *Proceedings of the IEEE*. 104(1): 148–175. DOI: 10.1109/jproc.2015.2494218.

Shang, Z., E. Zgraggen, B. Buratti, F. Kossmann, P. Eichmann, Y. Chung, C. Binnig, E. Upfal, and T. Kraska. (2019). "Democratizing Data Science through Interactive Curation of ML Pipelines". In: *Proceedings of the 2019 International Conference on Management of Data*. ACM. DOI: 10.1145/3299869.3319863.

Sharma, A., J. N. van Rijn, F. Hutter, and A. Müller. (2019). "Hyperparameter Importance for Image Classification by Residual Neural Networks". In: *Discovery Science*. Springer International Publishing. 112–126. DOI: 10.1007/978-3-030-33778-0_10.

Shi, X., J. Mueller, N. Erickson, M. Li, and A. Smola. (2021). "Multimodal AutoML on Structured Tables with Text Fields". In: *8th ICML Workshop on Automated Machine Learning (AutoML)*. URL: https://openreview.net/forum?id=OHAIVOOl7Vl.

Silva, S. R. and R. Silva. (2023). "FeatGeNN: Improving Model Performance for Tabular Data with Correlation-Based Feature Extraction". In: *Intelligent Systems*. Springer Nature Switzerland. 259–273. DOI: 10.1007/978-3-031-45368-7_17.

Siriborvornratanakul, T. (2022). "Human behavior in image-based Road Health Inspection Systems despite the emerging AutoML". *Journal of Big Data*. 9(1). DOI: 10.1186/s40537-022-00646-8.

Smith, M. R., L. Mitchell, C. Giraud-Carrier, and T. Martinez. (2014). "Recommending Learning Algorithms and Their Associated Hyperparameters". In: *Proceedings of the 2014 International Conference on Meta-Learning and Algorithm Selection - Volume 1201. MLAS'14*. Prague, Czech Republic: CEUR-WS.org. 39–40.

Smith-Miles, K. A. (2008). "Cross-disciplinary perspectives on meta-learning for algorithm selection". *ACM Computing Surveys*. 41(1): 1–25. DOI: 10.1145/1456650.1456656.

Snoek, J., H. Larochelle, and R. Adams. (2011). "Opportunity cost in Bayesian optimization". In: *NIPS Workshop on Bayesian Optimization, Sequential Experimental Design, and Bandits*.

Snoek, J., H. Larochelle, and R. P. Adams. (2012). “Practical Bayesian Optimization of Machine Learning Algorithms”. In: *Advances in Neural Information Processing Systems*. Ed. by F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger. Vol. 25. Curran Associates, Inc. 2951–2959. URL: https://proceedings.neurips.cc/paper/2012/file/05311655a15b75fab86956663e1819cd-Paper.pdf.

So, D., Q. Le, and C. Liang. (2019). “The Evolved Transformer”. In: *Proceedings of the 36th International Conference on Machine Learning*. Ed. by K. Chaudhuri and R. Salakhutdinov. Vol. 97. *Proceedings of Machine Learning Research*. PMLR. 5877–5886. URL: https://proceedings.mlr.press/v97/so19a.html.

Soares, C., J. Petrak, and P. Brazdil. (2001). “Sampling-Based Relative Landmarks: Systematically Test-Driving Algorithms before Choosing”. In: *Progress in Artificial Intelligence*. Springer Berlin Heidelberg. 88–95. DOI: 10.1007/3-540-45329-6_12.

Song, Q., H. Jin, and X. Hu. (2022). *Automated Machine Learning in Action*. MANNING PUBN. 300 pp. URL: https://www.ebook.de/de/product/41093518/qingquan_song_haifeng_jin_xia_hu_automated_machine_learning_in_action.html.

Sparks, E. R., A. Talwalkar, D. Haas, M. J. Franklin, M. I. Jordan, and T. Kraska. (2015). “Automating model search for large scale machine learning”. In: *Proceedings of the Sixth ACM Symposium on Cloud Computing - SoCC ’15*. ACM Press. DOI: 10.1145/2806777.2806945.

Sparks, E. R., S. Venkataraman, T. Kaftan, M. J. Franklin, and B. Recht. (2017). “KeystoneML: Optimizing Pipelines for Large-Scale Advanced Analytics”. In: *2017 IEEE 33rd International Conference on Data Engineering (ICDE)*. IEEE. DOI: 10.1109/icde.2017.109.

Sparks, E. R. (2016). “End-to-End Large Scale Machine Learning with KeystoneML”. *PhD thesis*. UC Berkeley.

Sprechmann, P., S. Jayakumar, J. Rae, A. Pritzel, A. P. Badia, B. Uria, O. Vinyals, D. Hassabis, R. Pascanu, and C. Blundell. (2018). “Memory-based Parameter Adaptation”. In: *International Conference on Learning Representations*. URL: https://openreview.net/forum?id=rkfOvGbCW.

Srivastava, S., B. Malone, N. Sukhija, I. Banicescu, and F. M. Ciorba. (2013). "Predicting the Flexibility of Dynamic Loop Scheduling Using an Artificial Neural Network". In: *2013 IEEE 12th International Symposium on Parallel and Distributed Computing*. IEEE. DOI: 10.1109/ispdc.2013.10.

Steinruecken, C., E. Smith, D. Janz, J. Lloyd, and Z. Ghahramani. (2019). "The Automatic Statistician". In: *Automated Machine Learning*. Springer International Publishing. 161–173. DOI: 10.1007/978-3-030-05318-5_9.

Studer, S., T. B. Bui, C. Drescher, A. Hanuschkin, L. Winkler, S. Peters, and K.-R. Müller. (2021). "Towards CRISP-ML(Q): A Machine Learning Process Model with Quality Assurance Methodology". *Machine Learning and Knowledge Extraction*. 3(2): 392–413. DOI: 10.3390/make3020020.

Suganuma, M., S. Shirakawa, and T. Nagao. (2017). "A genetic programming approach to designing convolutional neural network architectures". In: *Proceedings of the Genetic and Evolutionary Computation Conference*. ACM. DOI: 10.1145/3071178.3071229.

Sun, B., W. Cui, G. Liu, B. Zhou, and W. Zhao. (2023). "A hybrid strategy of AutoML and SHAP for automated and explainable concrete strength prediction". *Case Studies in Construction Materials*. 19: e02405. DOI: 10.1016/j.cscm.2023.e02405.

Sun, Q., B. Pfahringer, and M. Mayo. (2012). "Full model selection in the space of data mining operators". In: *Proceedings of the fourteenth international conference on Genetic and evolutionary computation conference companion - GECCO Companion '12*. ACM Press. DOI: 10.1145/2330784.2331014.

Sun, Q., B. Pfahringer, and M. Mayo. (2013). "Towards a Framework for Designing Full Model Selection and Optimization Systems". In: *Multiple Classifier Systems*. Springer Berlin Heidelberg. 259–270. DOI: 10.1007/978-3-642-38067-9_23.

Sun-Hosoya, L., I. Guyon, and M. Sebag. (2018a). "ActivMetaL: Algorithm Recommendation with Active Meta Learning". In: *IAL 2018 workshop, ECML PKDD*. URL: https://hal.archives-ouvertes.fr/hal-01931262.

Sun-Hosoya, L., I. Guyon, and M. Sebag. (2018b). "Lessons learned from the AutoML challenge". In: *Conférence sur l'Apprentissage Automatique 2018*. Rouen, France. URL: https://hal.inria.fr/hal-01811454.

Swearingen, T., W. Drevo, B. Cyphers, A. Cuesta-Infante, A. Ross, and K. Veeramachaneni. (2017). "ATM: A distributed, collaborative, scalable system for automated machine learning". In: *2017 IEEE International Conference on Big Data (Big Data)*. IEEE. DOI: 10.1109/bigdata.2017.8257923.

Swersky, K., J. Snoek, and R. P. Adams. (2013). "Multi-Task Bayesian Optimization". In: *Advances in Neural Information Processing Systems 26*. Ed. by C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger. Curran Associates, Inc. 2004–2012. URL: http://papers.nips.cc/paper/5086-multi-task-bayesian-optimization.pdf.

Takahashi, Y., M. Asahara, and K. Shudo. (2018). "A framework for searching a predictive model". In: *SysML Conference*. Vol. 2018.

Tantithamthavorn, C., S. McIntosh, A. E. Hassan, and K. Matsumoto. (2016). "Automated parameter optimization of classification techniques for defect prediction models". In: *Proceedings of the 38th International Conference on Software Engineering - ICSE '16*. ACM Press. DOI: 10.1145/2884781.2884857.

Tantithamthavorn, C., S. McIntosh, A. E. Hassan, and K. Matsumoto. (2019). "The Impact of Automated Parameter Optimization on Defect Prediction Models". *IEEE Transactions on Software Engineering*. 45(7): 683–711. DOI: 10.1109/tse.2018.2794977.

Teixeira, M. C. and G. L. Pappa. (2022). "Understanding AutoML search spaces with local optima networks". In: *Proceedings of the Genetic and Evolutionary Computation Conference*. ACM. DOI: 10.1145/3512290.3528743.

Thakur, A. and A. Krohn-Grimberghe. (2015). "AutoCompete: A Framework for Machine Learning Competition". *ArXiv*. arXiv: 1507.02188v1 [stat.ML].

Thomas, J., S. Coors, and B. Bischl. (2018). "Automatic Gradient Boosting". *ArXiv*. arXiv: 1807.03873v2 [stat.ML].

Thompson, W. R. (1933). "On the likelihood that one unknown probability exceeds another in view of the evidence of two samples". *Biometrika*. 25(3-4): 285–294. DOI: 10.1093/biomet/25.3-4.285.

Thornton, C., F. Hutter, H. H. Hoos, and K. Leyton-Brown. (2013). "Auto-WEKA: combined selection and hyperparameter optimization of classification algorithms". In: *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '13*. ACM Press. DOI: 10.1145/2487575.2487629.

Tornede, T., A. Tornede, J. Hanselle, F. Mohr, M. Wever, and E. Hüllermeier. (2023). "Towards Green Automated Machine Learning: Status Quo and Future Directions". *Journal of Artificial Intelligence Research*. 77: 427–457. DOI: 10.1613/jair.1.14340.

Truong, A., A. Walters, J. Goodsitt, K. Hines, C. B. Bruss, and R. Farivar. (2019). "Towards Automated Machine Learning: Evaluation and Comparison of AutoML Approaches and Tools". In: *2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)*. 1471–1479. DOI: 10.1109/ICTAI.2019.00209.

Tsakonas, A. and B. Gabrys. (2012). "GRADIENT: Grammar-driven genetic programming framework for building multi-component, hierarchical predictive systems". *Expert Systems with Applications*. 39(18): 13253–13266. DOI: 10.1016/j.eswa.2012.05.076.

Tsakonas, A. and B. Gabrys. (2013). "A fuzzy evolutionary framework for combining ensembles". *Applied Soft Computing*. 13(4): 1800–1812. DOI: 10.1016/j.asoc.2012.12.027.

Tu, R., N. Roberts, V. Prasad, S. Nayak, P. Jain, F. Sala, G. Ramakrishnan, A. Talwalkar, W. Neiswanger, and C. White. (2022). "AutoML for Climate Change: A Call to Action". *ArXiv*. DOI: 10.48550/ARXIV.2210.03324.

Tukey, J. W. (1962). "The Future of Data Analysis". *The Annals of Mathematical Statistics*. 33(1): 1–67. DOI: 10.1214/aoms/1177704711.

Ukil, A., I. Sahu, C. Puri, A. Mukherjee, R. Singh, S. Bandyopadhyay, and A. Pal. (2018). "AutoModeling: Integrated Approach for Automated Model Generation by Ensemble Selection of Feature Subset and Classifier". In: *2018 International Joint Conference on Neural Networks (IJCNN)*. IEEE. DOI: 10.1109/ijcnn.2018.8489730.

Vainshtein, R., A. Greenstein-Messica, G. Katz, B. Shapira, and L. Rokach. (2018). "A Hybrid Approach for Automatic Model Recommendation". In: *Proceedings of the 27th ACM International Conference on Information and Knowledge Management - CIKM '18*. ACM Press. DOI: 10.1145/3269206.3269299.

Vanschoren, J. (2011). "Meta-Learning Architectures: Collecting, Organizing and Exploiting Meta-Knowledge". In: *Studies in Computational Intelligence*. Springer Berlin Heidelberg. 117–155. DOI: 10.1007/978-3-642-20980-2_4.

Vanschoren, J. (2018). "Meta-Learning: A Survey". *ArXiv*. arXiv: 1810.03548v1 [cs.LG].

Vanschoren, J., J. N. van Rijn, B. Bischl, and L. Torgo. (2014). "OpenML: networked science in machine learning". *ACM SIGKDD Explorations Newsletter*. 15(2): 49–60. DOI: 10.1145/2641190.2641198.

Vega, A. de la, D. García-Saiz, M. Zorrilla, and P. Sánchez. (2019). "How Far are we from Data Mining Democratisation? A Systematic Review". *ArXiv*. Mar. arXiv: 1903.08431v1 [cs.DB].

Veloso, B., J. Gama, and B. Malheiro. (2018). "Self Hyper-Parameter Tuning for Data Streams". In: *Discovery Science*. Springer International Publishing. 241–255. DOI: 10.1007/978-3-030-01771-2_16.

Verma, S. and J. Rubin. (2018). "Fairness Definitions Explained". In: *2018 IEEE/ACM International Workshop on Software Fairness (FairWare)*. 1–7. DOI: 10.23919/FAIRWARE.2018.8452913.

Vilalta, R., C. G. Giraud-Carrier, P. Brazdil, and C. Soares. (2004). "Using Meta-Learning to Support Data Mining". *IJCSA*. 1(1): 31–45.

Wang, D., J. D. Weisz, M. Muller, P. Ram, W. Geyer, C. Dugan, Y. Tausczik, H. Samulowitz, and A. Gray. (2019). "Human-AI Collaboration in Data Science: Exploring Data Scientists' Perceptions of Automated AI". *Proceedings of the ACM on Human-Computer Interaction*. 3(CSCW): 1–24. DOI: 10.1145/3359313.

Wang, G., Q. Song, H. Sun, X. Zhang, B. Xu, and Y. Zhou. (2013). "A Feature Subset Selection Algorithm Automatic Recommendation Method". *Journal of Artificial Intelligence Research*. 47: 1–34. DOI: 10.1613/jair.3831.

Wang, L., M. Feng, B. Zhou, B. Xiang, and S. Mahadevan. (2015). "Efficient Hyper-parameter Optimization for NLP Applications". In: *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics. DOI: 10.18653/v1/d15-1253.

Wang, W. and K. Siau. (2019). "Artificial Intelligence, Machine Learning, Automation, Robotics, Future of Work and Future of Humanity". *Journal of Database Management*. 30(1): 61–79. DOI: 10.4018/jdm.2019010104.

Wang, Y., X. Zhao, T. Xu, and X. Wu. (2022). "AutoField: Automating Feature Selection in Deep Recommender Systems". In: *Proceedings of the ACM Web Conference 2022*. ACM. DOI: 10.1145/3485447.3512071.

Wever, M. D., F. Mohr, and E. Hüllermeier. (2018). "ML-Plan for Unlimited-Length Machine Learning Pipelines". In: *ICML 2018 AutoML Workshop*.

White, C., M. Safari, R. Sukthanker, B. Ru, T. Elsken, A. Zela, D. Dey, and F. Hutter. (2023). "Neural Architecture Search: Insights from 1000 Papers". *ArXiv*. DOI: 10.48550/ARXIV.2301.08727.

Wiener, N. (1960). "Some Moral and Technical Consequences of Automation". *Science*. 131(3410): 1355–1358. DOI: 10.1126/science.131.3410.1355.

Wistuba, M., A. Rawat, and T. Pedapati. (2019). "A Survey on Neural Architecture Search". *ArXiv*. May. arXiv: 1905.01392v2 [cs.LG].

Wistuba, M., N. Schilling, and L. Schmidt-Thieme. (2015a). "Hyperparameter Search Space Pruning – A New Component for Sequential Model-Based Hyperparameter Optimization". In: *Machine Learning and Knowledge Discovery in Databases*. Springer International Publishing. 104–119. DOI: 10.1007/978-3-319-23525-7_7.

Wistuba, M., N. Schilling, and L. Schmidt-Thieme. (2015b). "Learning hyperparameter optimization initializations". In: *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE. DOI: 10.1109/dsaa.2015.7344817.

Wistuba, M., N. Schilling, and L. Schmidt-Thieme. (2016). "Hyperparameter Optimization Machines". In: *2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE. DOI: 10.1109/dsaa.2016.12.

Wistuba, M., N. Schilling, and L. Schmidt-Thieme. (2017a). "Automatic Frankensteining: Creating Complex Ensembles Autonomously". In: *Proceedings of the 2017 SIAM International Conference on Data Mining*. Society for Industrial and Applied Mathematics. 741–749. DOI: 10.1137/1.9781611974973.83.

Wistuba, M., N. Schilling, and L. Schmidt-Thieme. (2017b). "Scalable Gaussian process-based transfer surrogates for hyperparameter optimization". *Machine Learning*. 107(1): 43–78. DOI: 10.1007/s10994-017-5684-y.

Wolpert, D. and W. Macready. (1997). "No free lunch theorems for optimization". *IEEE Transactions on Evolutionary Computation*. 1(1): 67–82. DOI: 10.1109/4235.585893.

Wolpert, D. H. (1996). "The Lack of A Priori Distinctions Between Learning Algorithms". *Neural Computation*. 8(7): 1341–1390. DOI: 10.1162/neco.1996.8.7.1341.

Wong, C., N. Houlsby, Y. Lu, and A. Gesmundo. (2018). "Transfer Learning with Neural AutoML". In: *Advances in Neural Information Processing Systems*. Ed. by S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett. Vol. 31. Curran Associates, Inc. 8356–8365. URL: https://proceedings.neurips.cc/paper/2018/file/bdb3c278f45e6734c35733d24299d3f4-Paper.pdf.

Wu, M.-S. and J.-Y. Lu. (2018). "Automated Machine Learning Algorithm Mining for Classification Problem". In: *Machine Learning and Data Mining in Pattern Recognition*. Springer International Publishing. 380–392. DOI: 10.1007/978-3-319-96136-1_30.

Xanthopoulos, I., I. Tsamardinos, V. Christophides, E. Simon, and A. Salinger. (2020). "Putting the Human Back in the AutoML Loop". In: *EDBT/ICDT Workshops*. Ed. by A. Poulovassilis, D. Auber, N. Bikakis, P. K. Chrysanthis, G. Papastefanatos, M. Sharaf, N. Pelekis, C. Renso, Y. Theodoridis, K. Zeitouni, T. Cerquitelli, S. Chiusano, G. Vargas-Solar, B. Omidvar-Tehrani, K. Morik, J.-M. Renders, D. Firmani, L. Tanca, D. Mottin, M. Lissandrini, and Y. Velegrakis. Vol. 2578. *CEUR Workshop Proceedings*. CEUR-WS.org. URL: http://ceur-ws.org/Vol-2578/ETMLP5.pdf.

Xu, M., Y. Zhao, K. Bian, G. Huang, Q. Mei, and X. Liu. (2020). "Federated Neural Architecture Search". *ArXiv*. Feb. arXiv: 2002.06352v4 [cs.LG].

Xue, B., M. Zhang, W. N. Browne, and X. Yao. (2016). "A Survey on Evolutionary Computation Approaches to Feature Selection". *IEEE Transactions on Evolutionary Computation*. 20(4): 606–626. DOI: 10.1109/tevc.2015.2504420.

Yang, C., J. Fan, Z. Wu, and M. Udell. (2020). "AutoML Pipeline Selection: Efficiently Navigating the Combinatorial Space". In: *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. ACM. DOI: 10.1145/3394486.3403197.

Yang, L. and A. Shami. (2020). "On Hyperparameter Optimization of Machine Learning Algorithms: Theory and Practice". *Neurocomputing*. DOI: 10.1016/j.neucom.2020.07.061.

Yang, L. and A. Shami. (2022). "IoT data analytics in dynamic environments: From an automated machine learning perspective". *Engineering Applications of Artificial Intelligence*. 116: 105366. DOI: 10.1016/j.engappai.2022.105366.

Yao, Q., M. Wang, Y. Chen, W. Dai, Y.-F. Li, W.-W. Tu, Q. Yang, and Y. Yu. (2018). "Taking Human out of Learning Applications: A Survey on Automated Machine Learning". *ArXiv*. arXiv: 1810.13306v4 [cs.AI].

Yao, X. (1999). "Evolving artificial neural networks". *Proceedings of the IEEE*. 87(9): 1423–1447. DOI: 10.1109/5.784219.

Yao, Y., Z. Xiao, B. Wang, B. Viswanath, H. Zheng, and B. Y. Zhao. (2017). "Complexity vs. performance: empirical analysis of machine learning as a service". In: *Proceedings of the 2017 Internet Measurement Conference on - IMC '17*. ACM Press. DOI: 10.1145/3131365.3131372.

Yogatama, D. and G. Mann. (2014). "Efficient Transfer Learning Method for Automatic Hyperparameter Tuning". In: *Proceedings of the Seventeenth International Conference on Artificial Intelligence and Statistics*. Ed. by S. Kaski and J. Corander. Vol. 33. *Proceedings of Machine Learning Research*. Reykjavik, Iceland: PMLR. 1077–1085. URL: http://proceedings.mlr.press/v33/yogatama14.html.

You, C., K. Guo, G. Feng, P. Yang, and T. Q. S. Quek. (2023). "Automated Federated Learning in Mobile-Edge Networks—Fast Adaptation and Convergence". *IEEE Internet of Things Journal*. 10(15): 13571–13586. DOI: 10.1109/jiot.2023.3262664.

Yu, C., B. Karlaš, J. Zhong, C. Zhang, and J. Liu. (2019). "AutoML from Service Provider's Perspective: Multi-device, Multi-tenant Model Selection with GP-EI". In: *Proceedings of Machine Learning Research*. Ed. by K. Chaudhuri and M. Sugiyama. Vol. 89. *Proceedings of Machine Learning Research*. PMLR. 2829–2838. URL: http://proceedings.mlr.press/v89/yu19e.html.

Yu, K., C. Sciuto, M. Jaggi, C. Musat, and M. Salzmann. (2020a). "Evaluating The Search Phase of Neural Architecture Search". In: *International Conference on Learning Representations*. URL: https://openreview.net/forum?id=H1loF2NFwr.

Yu, Z., Y. Cui, J. Yu, M. Wang, D. Tao, and Q. Tian. (2020b). "Deep Multimodal Neural Architecture Search". In: *Proceedings of the 28th ACM International Conference on Multimedia*. ACM. DOI: 10.1145/3394171.3413977.

Zela, A., A. Klein, S. Falkner, and F. Hutter. (2018). "Towards Automated Deep Learning: Efficient Joint Neural Architecture and Hyperparameter Search". *ArXiv*. arXiv: 1807.06906v1 [cs.LG].

Zeng, X. and G. Luo. (2017). "Progressive sampling-based Bayesian optimization for efficient and automatic machine learning model selection". *Health Information Science and Systems*. 5(1). DOI: 10.1007/s13755-017-0023-z.

Zhang, S., C. Gong, L. Wu, X. Liu, and M. Zhou. (2023). "AutoML-GPT: Automatic Machine Learning with GPT". *ArXiv*. DOI: 10.48550/ARXIV.2305.02499.

Zhang, Y., M. T. Bahadori, H. Su, and J. Sun. (2016). "FLASH: Fast Bayesian Optimization for Data Analytic Pipelines". In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '16*. ACM Press. DOI: 10.1145/2939672.2939829.

Zhao, Y., R. Zhang, and X. Li. (2022). "AutoDES: AutoML Pipeline Generation of Classification with Dynamic Ensemble Strategy Selection". *ArXiv*. DOI: 10.48550/ARXIV.2201.00207.

Zliobaite, I., A. Bifet, M. Gaber, B. Gabrys, J. Gama, L. Minku, and K. Musial. (2012). "Next challenges for adaptive learning systems". *ACM SIGKDD Explorations Newsletter*. 14(1): 48. DOI: 10.1145/2408736.2408746.

Zliobaite, I. and B. Gabrys. (2014). "Adaptive Preprocessing for Streaming Data". *IEEE Transactions on Knowledge and Data Engineering*. 26(2): 309–321. DOI: 10.1109/tkde.2012.147.

Žliobaitė, I., M. Budka, and F. Stahl. (2015). "Towards cost-sensitive adaptation: When is it worth updating your predictive model?" *Neurocomputing*. 150: 240–249. DOI: 10.1016/j.neucom.2014.05.084.

Zöller, M.-A. and M. F. Huber. (2021). "Benchmark and Survey of Automated Machine Learning Frameworks". *Journal of Artificial Intelligence Research*. 70: 409–472. DOI: 10.1613/jair.1.11854.

Zoph, B. and Q. V. Le. (2017). "Neural Architecture Search with Reinforcement Learning". In: *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. URL: https://openreview.net/forum?id=r1Ue8Hcxg.

Zoph, B., V. Vasudevan, J. Shlens, and Q. V. Le. (2018). "Learning Transferable Architectures for Scalable Image Recognition". In: *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. IEEE. DOI: 10.1109/cvpr.2018.00907.