Towards a Human-Centered Approach for Automating Data Science

Anamaria Crisan
Tableau Research
acrisan@tableau.com

Lars Kotthoff
University of Wyoming
larsko@uwyo.edu

Marc Streit
Johannes Kepler University Linz
marc.streit@jku.at

Kai Xu
University of Nottingham
kai.xu@nottingham.ac.uk

Abstract

Technology for Automating Data Science (AutoDS) consistently undervalues the role of human labor, resulting in tools that, at best, are ignored and, at worst, can actively mislead or even cause harm. Even if full and frictionless automation were possible, human oversight is still desired and required to review the outputs of AutoDS tooling and integrate them into decision-making processes. We propose a human-centered lens to AutoDS that emphasizes the collaborative relationships between humans and these automated processes and elevates the effects these interactions have on downstream decision-making. Our approach leverages a provenance framework that integrates user-, data-, and model-centric approaches to make AutoDS platforms observable and interrogable by humans.

1 The need for Automation in Data Science (AutoDS)

The scope of Automated Data Science (AutoDS) technology has extended beyond its initial boundaries of model selection and hyperparameter tuning and toward end-to-end development and refinement of data science pipelines [6, 2, 5, 13]. These advances, both theoretical and realized, make the tools of data science more readily available to domain experts that rely on low, or no-code, tooling options to analyze and make sense of their data. However, AutoDS tools cannot function without user intervention, such as setting the objective functions, ensuring data quality, and identifying causes and possible improvements when the overall performance is poor [10, 2, 11, 6]. Even if full automation were possible, it is not always desirable. There is an increasing body of literature showing that incorporating the knowledge and experiences of domain experts can considerably improve the model performance [1, 12]. Moreover, there is also a demand for human oversight and intervention to meet the growing regulations [4, 9, 3]. However, human intervention is rarely a design consideration for AutoDS tooling. To ensure that AutoDS technologies are applied both effectively and responsibly, it becomes increasingly urgent to carefully audit the decisions made both automatically and with human guidance.

2 AutoDS requires Human-AI Interaction

Automating data science involves a patchwork pipeline that trades-off tasks between User and Model processes, often with Data as an intermediary substrate. As an example, an analyst wishing to develop a new model to predict customer churn may go through several iterations of data gathering, model development and optimization, and finally iterative feedback from fellow stakeholders. In Figure 1 we provide an example such a trade-off that illustrates points of interaction between humans and these automated processes, which we collectively refer to as Human-AI Interaction (HAI). There are different modalities for HAI along an AutoDS pipeline, which we can broadly define as ***inter*-process** and ***intra*-process** phases the trade-off tasks and data.

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***Inter*-process** interactions orchestrate the transfer or tasks between boundaries of users, data, and models. For example, an analyst defines a task and dataset that is then provided as input to an AutoDS tool for analysis; such a flow could be described as → → . The sequence can also operate in reverse, where data outputted from the AutoDS tool is provided to a user for review. Data need not always serve as an intermediary, for example, a user may provide initialization parameters to an AutoDS tool (→). Over time, the complexity of these interaction sequences grows as more tasks and data are passed between User and Model. Currently, supporting these inter-processes transitions remains limited and is often fragile.

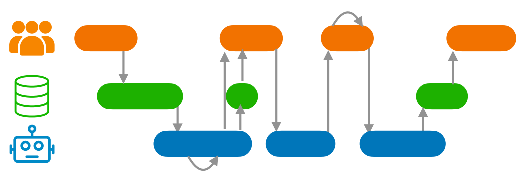

Figure 1: Illustrative example of an HAI process between User, Data, and Model that occurs even when data science work is automated.

Equally important, but frequently overlooked, are the ***intra*-process** tasks that occur *within* user (→) or automation (→) processes. Data Science is a team sport, requiring not only multiple data scientists but other less technical stakeholders that are also involved in data work. Data and analysis results are shared and discussed among users and the resulting consensus reached from these discussions results in interventions that cross boundaries (i.e, →). Similarly, AutoDS processes involve complex steps, especially as the capabilities of such systems evolve beyond algorithm selection and involve learning more end-to-end pipelines from data preparation to deployment. Existing auditing and provenance tooling, including those that visualize AutoDS pipelines, are catered towards → steps but overlook → processes that are equally influential in producing the final results.

3 AutoDS must be observable and interrogable

The full portrait of an AutoDS is a complex sequence of events where tasks and data move between inter-process steps and within intra-process steps. Over time, it becomes difficult to understand how the results were generated and influenced downstream decisions. This gap reveals that AutoDS must facilitate a mutual understanding between the automated analysis and end users, and the ability for the two parties to communicate and collaborate effectively. This requires not only information on **what** data have been used and **how** the analysis is done, but also the context such as **when** it is done by **whom** and more importantly **why** choices and decisions are made.

At present, we have limited ability to capture this information and surface the lineage of decision-making in some meaningful way. Existing methodologies for provenance in data analysis focus on User, Data, and Model separately, but should be explored together in AutoDS to be fully transparent and auditable. However, modalities of capturing User, Data, and Model provenance may not always align and there exist few techniques that attempt their integration. User provenance can be especially complex as the thinking and reasoning behind analysis choices and decisions are challenging to capture.

4 Human-Centered AutoDS

By acknowledging that humans and automated processes must collaborate in AutoDS, we must explicitly consider the needs of humans to understand and intervene. Without these considerations, AutoDS systems risk being discarded or even misleading end-users with potentially erroneous results that are difficult to trace. We see potential to leverage a provenance-based approach to advancing human-centered objectives for AutoDS technology. This approach captures and surfaces artifacts that result from an end-to-end AutoDS process, from data collection to model deployment [8, 7]. We propose further augmenting provenance through the integration of user-, data-, and model-centric perspectives, we can derive a more complete and holistic view of AutoDS that enables humans to build, monitor, and intervene in the actions of increasingly complex AI/ML technology.

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