AutoDS: Towards Human-Centered Automation of Data Science

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ABSTRACT

Data science (DS) projects often follow a lifecycle that consists of laborious tasks for data scientists and domain experts (e.g., data exploration, model training, etc.). Only till recently, machine learning (ML) researchers have developed promising automation techniques to aid data workers in these tasks. This paper introduces AutoDS, an automated machine learning (AutoML) system that aims to leverage the latest ML automation techniques to support data science projects. Data workers only need to upload their dataset, then the system can automatically suggest ML configurations, preprocess data, select algorithm, and train the model. These suggestions are presented to the user via a web-based graphical user interface and a notebook-based programming user interface. We studied AutoDS with 30 professional data scientists, where one group used AutoDS, and the other did not, to complete a data science project. As expected, AutoDS improves productivity; Yet surprisingly, we find that the models produced by the AutoDS group have higher quality and less errors, but lower human confidence scores. We reflect on the findings by presenting design implications for incorporating automation techniques into human work in the data science lifecycle.

CCS CONCEPTS

• Human-centered computing → User studies; Empirical studies in HCI; • Computing methodologies → Artificial intelligence.

KEYWORDS

Data science, automated data science, automated machine learning, AutoML, AutoDS, model building, human-in-the-loop, AI, human-AI collaboration, XAI, collaborative AI

1 INTRODUCTION AND BACKGROUND

Data Science (DS) refers to the practice of applying statistical and machine learning approaches to analyze data and generate insights for decision making or knowledge discovery [11, 44, 48]. It involves a wide range of tasks from understanding a technical problem to coding and training a machine learning model [48, 65]. Together, these steps constitute a data science project’s lifecycle [63]. As illustrated in Figure 1, data science literature often use a circle diagram to represent the entire data science life cycle. In one version of the DS lifecycle model, [63] synthesizes multiple papers and suggests a 10 Stages view of the DS work. Because the complex natural of a DS lifecycle, a DS project often requires an interdisciplinary DS team (e.g., domain experts and data scientists) [29, 52, 70]. Previous literature suggests that as much as 80% of a DS team’s time [55] is spent on low-level activities, such as manually tweaking data [25] or trying to select various candidate algorithms [71] with python and Jupyter notebooks [30]; thus, they do not have enough time for valuable knowledge discovery activities to create better models. To cope with this challenge, researchers have started exploring the use of ML algorithms (i.e., Bayesian optimization) to automate the low-level activities, such as automatically training and selecting the best algorithm from all the candidates [35, 38, 40, 71]; this group of work is called Automated Data Science (or AutoDS for short) 1.

Many research communities, universities, and companies have recently made significant investments in AutoDS research, under the belief that the world has ample data and, therefore, an unprecedented demand for data scientists [24]. For example, Google released AutoML in 2018 [19]. Startups like H2O [23] and Data Robot [10] both have their branded products. There are also Auto-sklearn [16] and TPOT [14, 50] from the open source communities.

While ML researchers and practitioners keep investing and advancing the AutoDS technologies, HCI researchers have begun to investigate how these AI systems may change the future of data scientists’ work. For example, a recent qualitative study revealed data scientists’ attitudes and perceived interactions with AutoDS systems is beginning to shift to a collaborative mindset, rather than a competitive one, where the relationship between data scientists and AutoDS systems, cautiously opens the “inevitable future of automated data science” [65].

However, little is known about how data scientists would actually interact with an AutoDS system to solve data science problems. To fill this gap, we designed the AutoDS system and

1 Some researchers also refer to Automated Artificial Intelligence (AutoAI) or Automated Machine Learning (AutoML). In this paper, we use AutoDS to refer to the collection of all these technologies.
conducted a between-subject user study to learn how data workers use it in practice. We recruited 30 professional data scientists and assigned them into one of two groups to complete the same task — using up to 30 minutes to build the best performing model for the given dataset. Half of the participants used AutoDS (experiment group), and the other half built models using Python in a Jupyter notebook, which aims to replicate their daily model building work practice (control group). We collected various measurements to quantify 1) the participant’s productivity (e.g., how long a participant spent in building the model or improving the model), 2) the final model’s performance (e.g., its accuracy), and 3) the participant’s confidence score in the final model (i.e., how much confidence a participant has in the final model, if they are asked to deploy their model). Before the experiment, we also collect measurements on 4) each participant’s data expertise level and 5) their prior experience and general attitude towards AutoDS as control variables.

Our results show that, as expected, the participants with AutoDS support can create more models (on average 8 models v.s. 3.13 models) and much faster (on average 5 minutes v.s. 15 minutes), than the participants with python and notebook. More interestingly, the final models from the AutoDS group have higher quality (.919 ROC AUC v.s .899) and less human errors (0 out of 15 v.s 7 out of 15), than the models from the control group with python and notebooks. The most intriguing finding is that despite participants acknowledged the AutoDS models were at better quality, they had lower confidence scores in these models than in the manually-crafted models, if they were to deploy the model (2.4 v.s. 3.3 out of a 5-point Likert scale). This result indicates that “better” models are not equal to “confident” models, and the “trustworthiness” of AutoDS is critical for user adoption in the future. We discuss the potential explanations for this seemingly conflicted result, and design implications stemming from it.

In summary, our work makes the following contributions to the CHI community:
- We present an automated data science prototype system with various novel feature designs (e.g., end-to-end, human-in-the-loop, and automatically exporting models to notebooks);
- We offer a systematic investigation of user interaction and perceptions of using an AutoDS system in solving a data science task, which yields many expected (e.g., higher productivity) and novel findings (e.g., performance is not equal to confidence, and shift of focus); and
- Based on these novel findings, we present design implications for AutoDS systems to better fit into data science workers’ workflow.

2 RELATED WORK

2.1 Human-Centered Machine Learning

Many researchers have studied how data scientists work with data and models. For example, it was suggested that 80 percent of the time spent on a data science project is spent in data preparation [22, 48, 70, 71]. As a result, data scientists often do not have enough time to complete a comprehensive data analysis [61].

A popular research topic in this domain is interactive machine learning, which aims to design better user experiences for human users to interact with machine learning tool [1]. These human users are often labelers of a data sample or domain experts who have better domain knowledge but not so much machine learning expertise.

Based on these the findings from these empirical studies, many tools have been built to support data science workers’ work [34, 44, 53]. For example, Jupyter Notebook [30] and its variations such as Google Colab [20] and Jupyter-Lab [31] are widely adopted by the data science community. These systems provide an easy code-and-test environment with a graphical user interface so that data scientists can quickly iterate their model crafting and testing process [37, 48]. Another group of tools includes the Data Voyager [26] and TensorBoard [9] systems that provide visual analytic support to data scientists to explore their data, but they often stop in the data preparation stage and thus do not provide automated support for model building tasks in the lifecycle (as shown in Figure 1).

2.2 Human-in-the-Loop AutoDS

AutoDS refers to a group of technologies that can automate the manual processes of data pre-processing, feature engineering, model selection, etc. [71]. Several technologies have been developed with different specializations. For example, Google has developed a set of AutoDS products under the umbrella of Cloud AutoML, such that even non-technical users can build models for visual, text, and tabular data [19]. H2O is java-based software for data modelling that provides a python module, which data scientists can import into their code file in order to use the automation capability [23].

Despite the extensive work in building AutoDS systems and algorithms, only a few recent efforts have focused on the interaction between humans and AutoDS. Gil and collaborators propose a guideline for designing AutoDS systems [18]. However, they envision new design features for AutoDS based on their understanding.
of how data scientists manually build models, and their understandings arise from surveying the previous literature and the authors’ personal experience. In our study, we aim to fill in the empirical understanding gap by conduct an experiment to systematically examine how data scientists actually use an AutoDS system.

Another recent work studies data scientists’ perceptions and attitudes towards AutoDS systems through an interview with 30 data scientists [65]. The interviewees, who have never interacted with AutoDS before, believe that AutoDS could potentially change their work practice. They also believe automation in data science work is the future, but they certainly hope that such automation could support their jobs instead of sabotaging them. We follow this line of research. We aim to provide an account for the actual user behaviors when a data scientist uses an AutoDS system to build a model.

There is one more research strand worth mentioning is the information visualization designs for AutoDS systems [67, 68]. For example, ATMSeer enables users to browse AutoDS processes at the algorithm, hyperpartition, and hyperparameter levels [71]. Their results indicate that users with a higher level of expertise in machine learning are more willing to interact with ATMSeer [67]. We reference these existing visualization work’s findings while designing and implementing our prototype system’s user interface. But these papers only focus on the visualization aspect and reveal information on existing AutoDS pipelines, and they do not measure the data scientists’ behaviors. Thus, the feedback from these studies are limited to the AutoDS visualization user interface design, but not much for the AutoDS’s functionality improvement.

2.3 Human-Centered AI Design and “Cooperative” AI

The recent “AI Summer” [21] is remarked with machine learning system demonstrations such as IBM DeepBlue [6] and Watson Jeopardy [45], and Google’s AlphaGo [66]. In these user scenarios, AI has largely been portrayed as a competitor to humans. The general public and news media began to worry about when the “singularity” will arrive, with AI replacing humans [3].

More recently, a few researchers have started to argue that instead of worrying about the singularity, why do we not work together to design AI systems that can collaborate with humans? [42, 59] Following this trend, HCI projects have reported various case studies of designing AI systems to work together with humans instead of replacing them. For example, Cranshaw and collaborators developed a calendar scheduling assistant system that combines the complementary capabilities of humans and AI for tasks such as scheduling meetings [8]. They coined this architecture a “human-in-the-loop AI system”. More towards the hardware side of the AI spectrum, a group of researchers from Cornell University have designed a robot that can work together with humans as a team and complete the tasks such as distributing resources to human collaborators [7]. IBM researchers also experimented the use case of putting an embodied conversational agent into a recruiting team of two human participants, with the agent and humans working together to complete a CV review task [57].

There was a seminal debate 20 years ago on “Agency v.s. Direct Manipulation User Interfaces Design” [58]. With more and more deep neural network AI technologies, we, as human users, find it harder and harder to understand what happens inside the AI “black box”. In parallel, we designate more and more agency and proactiveness to many of today’s AI system user interfaces, such as the conversational systems and autonomous cars. Some researchers have reported that users already look at these AI systems differently than the traditional computer systems but more like human partners [69], where anthropomorphism effect plays a critical role in user perceptions (e.g. [49, 62]. Researchers and designers are actively asking: what are the updated frameworks and theories that we can leverage to help us design better AI systems to work with human?

Various human-centered design guidelines for AI have been published in the past year from big companies such as Google, Microsoft, and IBM [2, 28, 56, 60]. But these guidelines often focus only on usability of AI system’s interface design, but fall short in discussing the integration of AI systems into human workflows as a collaborative partner. We argue that with an AI system being perceived more like a collaborator teaming up with humans, we may be able to reference classical theories from human-human collaborations to guide our design of an cooperative AI system. For example, we may learn from the “collaboration awareness” concept [12] to guide our design of AI system’s “transparency”. The “awareness” is a bi-directional concept, thus maybe “transparent AI” should not only have human better understand AI’s runtime state and logic, but also have AI keep track of human’s states and intention. Thus, in this study, we are also interested in exploring the human-AutoDS interaction through a collaborative work perspective.

3 AUTODS SYSTEM DESIGN

Based on machine learning technique’s advances and inspired by design insights from related literature, we implement an AutoDS prototype system, shown in Figure 2, to support data science workers on data science tasks.

From the user perceptive, a user is only required to upload their dataset to trigger the AutoDS execution, and then they can wait for the final model result. They interact with the system primarily from two graphical user interface screens: a configuration screen (Figure 2a) and a result screen (Figure 2b). At the configuration screen, after the user uploads a dataset, AutoDS suggests a specific ML task configuration for users to approve or adjust (e.g., classification or regression); then at the result screen, the users can monitor AutoDS’s execution progress visualization in real time and eventually see the final results in a model leaderboard view.

When looking closer at the result screen in Figure 2b, we design a tree-based progress visualization at the top. Each leaf node in the tree-based visualization represents one of the candidate model pipeline; and the path represents its composition flow. The screenshot illustrates an AutoDS execution is in progress. Two algorithms are being tested (XGB Classifier (blue) and Gradient Boosting Classifier (purple)). For the XGB Classifier, four models (P1 to P4) are generated; and for Gradient Boosting Classifier, only two models (P5 and P6) are generated, and two more (P7 and P8) are in training. Some models use the same algorithm but their composition steps are different. For example, P2 has an extra step of hyperparameter...
optimization, in comparison to P1, and P3 has an additional feature engineering step, despite these models are all using the same XGB algorithm.

At the bottom of the result screen in Figure 2b, we included a model result leaderboard. Each row in the leaderboard represents a candidate model pipeline, which corresponds to a model node in the tree visualization at the top. It displays following model information: Rank, Pipeline ID, Algorithm, Accuracy Score, Enhancement Steps such as Transformation and HyperparameterOptimization, Training Runtime, and ROC AUC model performance score on training or holdout data splits.

We design three user functions for each model result, and they all can be triggered through interacting with the model leaderboard. 1) a user can further examine the details of a model (such as the features included or excluded in the model, the prediction plot, etc) through clicking on a row in the leaderboard (not shown in Figure 2b); 2) if a user is satisfied with a model, they can click on the “Save as” button to save the “Model” (shown in Figure 2b), which will be automatically deployed as a Cloud API endpoint; and 3) if a user is interested in checking the details of a model via python notebook, they can click on “Save as Notebook” button (shown in Figure 2b) and download the AutoDS-generated notebook for further improvement. Many of these design consideration (e.g., automatic generation of human-readable python notebooks) are also novel and practical contributions to the AutoDS system designs.

From the system and algorithm perspective, AutoDS reads in the user uploaded dataset, suggests a problem configuration (e.g., classification or regression) based on the data structure. Then, AutoDS jointly optimizes the sequence of the model pipeline, which includes selecting the appropriate methods for data preprocessing, feature engineering, algorithm selection, and hyperparameter optimization. AutoDS can choose a sequence of transformation steps before training an estimator, or it can simply decide not to use any transformation to generate new features. Once the sequence is decided, AutoDS can search and decide on which particular transformation to be used inside each of the transformation step, and which estimator to be used inside the modeling step. Finally, AutoDS will fine-tune the hyperparameters of those chosen estimators and transformations simultaneously.

By design, our AutoDS system can provide automation support for the end-to-end data science lifecycle as shown in Fig. 1: from Requirement Gathering and Problem Formulation (i.e., suggesting configurations), to Model Building and Training (i.e., selecting algorithms), and to Decision Making and Optimization (i.e., deploying models).

4 METHOD

4.1 Experiment Design

Following a lab experiment study guideline [17], we conducted a between-subject user evaluation to understand how people interact with AutoDS in a data science project. Participants were asked to try their best at building a machine learning model for the same UCI Heart Disease dataset [5], either by writing Python code in a Jupyter Notebook (Notebook Condition in Figure 3) or by using the AutoDS prototype system (AutoDS Condition in Figure 2).

The experiment design follows a time-constrained clinical trial setting, each participants was given 30 minutes to build their best model. The reason why we decided on 30 minutes was because that from our three pilot study sessions, all the pilot participants (data scientists) finished the task within 12 minutes, and they needed to write no more than 10 lines of code to get the expected result: split train and test data subsets, define a model variable, and run a cross-validation function to train the model and report the accuracy score. We considered a participant having completed the task if s/he got at least one model.

Their final model’s performance is evaluated based on the ROC AUC score. During the 30 minutes time, participants were allowed to try out one or more models, but they understood that their performance and productivity was not measured by the quantity of the model, rather the quality of the model. They were allowed to submit early if they were satisfied with the model. All experiment sessions were conducted remotely using a video conferencing system, and participants used their own laptops during the experiment, as both the notebook and AutoDS were hosted on our experiment cloud server. These requirement was specified in the experiment

For more technical details about the AutoDS joint optimization algorithm, readers can refer to [38, 43] to replicate the backend.

One of the widely-used model performance metrics [51]. For simplicity, we refer to this metric as “accuracy” in the rest of paper.
instruction and all the participants verbally acknowledged this requirement.

Worthy noting that this data science task is a simplified version of their daily data science works, we selected the UCI Heart Disease dataset, which contains only 303 patients’ basic medical record information and 13 features (both continuous and categorical values) to predict whether the patients have heart disease (binary target feature with 0 represents no disease). It was a widely used benchmark dataset in research papers as well as in machine learning competitions (e.g., Kaggle [32]). Data cleaning, preprocessing, and feature engineering steps are not critical to build a valid model, but in order to achieve better model performance, participants do need to try out further model improvement steps. In both conditions, the dataset and required libraries in Notebook were pre-loaded so participants did not need to find the data or set up the network.

We asked the participants to share their screens, and with their consent, we recorded each session for further analysis.

4.2 AutoDS Condition
Participants in the AutoDS Condition used our AutoDS prototype, shown in Figure 2. As a default problem configuration, AutoDS can generate a list of the four model pipelines with one single algorithm (shown in Fig. 2). A model pipeline consists of all of the composition steps in generating the model, from reading data to optimizing hyperparameters. As aforementioned, not all pipelines had the hyperparameter optimization step or feature engineering step, leading to the variety of generated models and their accuracy scores. Participants could modify the AutoDS's configuration and get up to 8 model pipelines.

As shown in the AutoDS system design section, participants have a user function to inspect the generated model results with a visualization and a leaderboard showing information such as the confusion matrix, a feature importance chart, and tables with various evaluation metrics (e.g. ROC AUC, precision, F1, etc.) and descriptions of feature transformations. In addition, through the automated notebook generation feature in AutoDS systems, participants were also able to download, execute, or edit the generated code and to further improve the AutoDS model through coding.

4.3 Notebook Condition
Participants in the Notebook Condition were provided with an online Jupyter Notebook environment as a replication to their current work environment. To simplify the task, we provided notebooks with pre-scripted code sections and a skeleton of instructions. The notebooks were pre-loaded with data and necessary libraries, and we provided instructions in the markdown cells in different sections. For example, we listed ”(Optional) Feature Engineering section”, ”(Required) Modeling Training and Selection section”, and blank code cells for users to fill in their code. In the model training and selection section, we suggested five commonly used algorithms for this particular task: Logistic Classifier, KNN, SVM, Decision Tree, and Random Forest [51]. Noted that these pre-scripted code skeletons were meant to help participants to easily write code, and we specifically described in the task sheet that they were not enforced to use these pre-scripted codes. From our observation of the experiment, some participants in the Notebook Condition did choose to not use the skeleton but wrote all codes in one cell.

4.4 Measures
Our research goal was to explore how different the participants (i.e. data scientists) may complete the data science tasks in these two conditions. To that goal, we manually coded the 30 video recording sessions (each is at 45 minutes to one hour long) to extract various measurements, such as how many models each participant generated, what final algorithm they selected, and what its accuracy was. We also captured time-related measures, such as how long they spent on the model building task, to evaluate how participants allocate their time differently.

In both AutoDS Condition and Notebook Condition, we collected participants background information and their attitudes and perception towards AutoDS before the session. We also collected their confidence score of the final submitted model after the session.

In the AutoDS Condition alone, we also collected participants’ perceptions towards the AutoDS prototype they just used through a XAI questionnaire [27], as its four dimensions of predictable, reliable, efficient, and believable of an AI system is applicable in our context. In addition, we also collected participants’ ratings of trust in AutoDS technologies for a second time in the AutoDS condition, as their scores may change after just experiencing the system. Thus, we can compare the two pre-study trust scores across the two conditions, and compare the pre-study and post-study trust scores in the AutoDS Condition.

It is worth noting that we collect ROC AUC score among other scores as an indicator of the model performance from both conditions, as we simply need a standardized metric to reflect each
We recruited 30 professional data scientists in a multinational IT company, and randomly assigned them to one of the two conditions (AutoDS vs. Notebook). These participants come from different locations in the U.S., South Africa, and Australia. Seven participants out of 30 were female (23%), which was similar to the 16.8% ratio reported in the Kaggle 2018 survey of data science [33].

Our recruitment criteria was that the participants were professional data scientists and that they practiced data science or machine learning works in their day-to-day work. Participants reported practicing data science for an average of 3.5 years (SD = 2.7). Six participants (20%) rated themselves as beginners, 17 (57%) as intermediates, and 7 (23%) as experts in data science. Participants rated themselves at a moderate amount of experience (3.2 SD=.97 out of 5) with python scikit-learn lib, which is used in our study. Later, in the modeling section in result section 5.5.2, we test whether these background factors (e.g., years of expertise, and prior experience with scikit-learn) may influence the model performance, and the result is not significant.

In summary, we have four groups of quantitative measurements:

- Participant’s background information, collected via a pre-study survey (P1, P2 for both conditions);
- Participant’s perceptions toward general AutoDS type of technologies, collected via a pre-study survey (A1, A2, A3 for both conditions) and post-study survey (AA2, AA3, AA5 for AutoDS condition only)
- Participant’s behavioral measurements in the task (B3, BNx, BAx) and the final model performance (B1, B2), collected via coding the video recordings (both conditions)
- Whether the participant successfully completed the task without human error, collected by examining the final model’s code (F1 for both conditions)

A summary of all the collected quantitative measurements are listed in Table 1. We also conducted a semi-structured interview at the end of each session to gather users’ qualitative feedback to enrich our results.

4.5 Participants

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5 RESULTS

We first describe the overall results, then we list results in the order of: attitudes toward general AutoDS systems; behavioral measures from Notebook conditions and from AutoDS conditions respectively; and lastly, an extensive comparison of the two conditions in terms of participant behaviors, model outcomes, and participant attitudes.

5.1 Overall Results

All 15 participants (100%) in the AutoDS condition and eight participants (53%) in the Notebook condition finished the model building task without any human error. We refered to these participants as the “successful” participants. In contrast, seven participants (47%) from the Notebook condition made one or more mistakes in the process. Common human errors included the participant forgetting to split the dataset into training and testing subsets, or reporting a different accuracy metric other than the required ROC AUC score.

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| Table 1: Summary of background, behavioral, and attitudinal measures captured in the study. |
| --- |
| **Background Measures** |
| P1. Years spent practicing data science |
| P2. Prior experience with scikit-learn (1=low, 5=high) |
| **Attitudinal Measures** |
| “A” questions used in both conditions, “AA” used only in AutoDS |
| A1. Previous familiarity with general AutoDS (1=low, 5=high) |
| A2. Trust in general AutoDS (first time) |
| A2A. Trust in general AutoDS (second time) |
| A3. Belief in general AutoDS replace human (first time) |
| A3A. Belief in general AutoDS replace human (second time) |
| A4. Participant’s confidence in the selected final model |
| AA5. XAI Scale [27] |
| **Behavioral Measures** |
| “B” questions used in both conditions, “BA” used only in AutoDS, “BN” used only in Notebook |
| B1. Accuracy of final model (ROC AUC) |
| B2. Type of final model (e.g. logistic regression, random forest, etc.) |
| B3. Total time spent searching for information on the web |
| BN1. Amount of time spent preparing data |
| BN2. Amount of time spent until the first model was produced |
| BN3. Number of different models tried |
| BN4. Did participant perform exploratory data analysis (EDA)? |
| BN5. Did participant perform feature engineering? |
| BA1. Total time spent configuring AutoDS |
| BA2. Total time spent running AutoDS |
| BA3. Total time spent examining the leaderboard |
| BA4. Total time spent examining pipeline details |
| BA5. Number of times AutoDS was run |
| BA6. Number of pipelines examined (i.e. viewed pipeline details) |
| BA7. Number of pipeline notebooks viewed |
| BA8. Number of pipeline notebooks edited |
| BA9. Which AutoDS pipeline was chosen at the end? |
| BA10. Did participant change the code of the final selected pipeline? |
| BA11. Accuracy of the modified pipeline |
| **Successful Completion** |
| F1. (Binary) Did participant successfully complete the task without human error (e.g., mistakenly reporting accuracy score from the training data split instead of the holdout)? |
The experiment time was limited up to 30 minutes for both the conditions, out of all 30 participants, the fastest participant to reach a state of completion was P23 (Notebook), who finished the task early in 17.9 minutes with an accuracy score of 0.923. This was an extraordinarily good performance of human data scientists in the Notebook condition, because, on average, participants spent 15 minutes (SD = 6.8 minutes) generating 1 model (BN2). For comparison, AutoDS condition participants generated 4 model pipelines in about 5 minutes. If the productivity of building a model were to be measured by the time and the quantity, this result could have been seen as "AutoDS brings a 300% increase in productivity". But this result was not the goal of our study and it was kinds of expected. Also, it was not a fair comparison, thus we would caution readers not to use this number bluntly.

As for final submitted models, 18 participants chose the Random Forest algorithm (also the best one according to our own experiment), 9 chose Logistic Regression, 2 used SVM and 1 chose Extra-Tree. The AutoDS condition outcome was dominated by Random Forest (13 out of 15) with 2 participants chose Logistic regression. In the Notebook condition, participants’ choices were more diverse with only 5 out of 15 chose Random Forest.

5.2 Attitudes Toward AutoDS

Before the task, participants in both conditions were asked their familiarity and attitudes toward general AutoDS technologies (A1, A2, A3); at the end of the AutoDS condition, participants were again asked about the attitudes questions (AA2, AA3). In this section, we report the comparison between A1, A2, A3 measurements between the two conditions. We reserve the comparison result between pre-study trust and post-study trust inside the AutoDS condition in Sec 5.5.4. In general, participants had some familiarity with AutoDS/AutoML technologies (2.27 SD = 1.08 out of 5), but not much. They may have heard about it before or even used it once, but they had not been using it frequently (A1).

About the "Trust in General AutoDS/AutoML" question (A2), we found participants had conflicting opinions: 13 participants (43%) agreed with this statement, 13 remained neutral, and 4 disagreed (13%).

And lastly, participants did not believe AutoDS would replace human data scientists (A3): 15 (50%) disagreed with this statement and only 3 (10%) agreed, with the rest remaining neutral.

5.3 How Data Scientists Worked with AutoDS

In this subsection, we report how participants built models using AutoDS.

Participants needed to explore the data to understand the problem; they did so in the AutoDS configuration step. Thus, despite AutoDS automatically and instantly suggested default configurations (such as prediction type), participants still spent some time in this step to further examine the dataset by checking the data distributions etc. (2.3 SD = .96 min) (BA1).

Feature engineering, model training, and model selection steps were fully automated by AutoDS; we tracked time as participants waited for AutoDS to complete runs (2.1 SD = .59 min) (BA2).

“It’s fast and it gives you visualizations to compare the models, this saves me a lot of time” (P8, M, AutoDS)

Because it was fast for data scientists in the AutoDS condition to generate models (in total less than 5 minutes), participants had some extra time to spend on other activities (BA3). For example, they spent more time to examine or further refine the model pipeline results generated by AutoDS. They spent most of their time in examining the leaderboard and visualization as shown in Figure ?? (9.7 SD = 3.4 min) (BA3). Then, they also went into particular model’s detailed information page for fine-grained information (3.9 SD = 2.2 min) (BA4).

Participants examined the details of an average of 3.8 (SD = 1.2) pipelines (BA6), and some of them downloaded the generated notebook, examined the code to further understand the model (7 out 15 participants, spent an average of 2.3 (SD = .70 minutes) (BA7). Some participants even further revised those codes (7 out 15), and most of these participants edited only one Notebook (BA8). Participants who chose to edit code did so with mixed outcome results. Out of 7, two were able to improve accuracy scores to the pipeline produced by AutoDS, and two submitted final models that actually had slightly worse accuracy. Three abandoned their changes and submitted the original scores (BA10).

The path of selecting the best model in AutoDS condition seemed straightforward: a participant ran AutoDS and selected the model with the "highest performance AUC ROC score". But some participants did not select the top performance model as their final choice. Of the 8 possible models that could be produced with AutoDS, 8 participants chose the highest-scoring one (called "P") with a Random Forest algorithm, and 7 chose a different model with a lower ROC AUC score than P7. It appears that even though P7 with the highest ROC AUC score was available to the participant, in some cases they had already invested time and effort in inspecting and tweaking parameters within an earlier generated pipeline, in the end selecting a pipeline with a lower ROC AUC score than P7 (BA9). The mean ROC AUC score for the final selected model was 0.919 (SD = .01) (BA11).

5.4 How Data Scientists Work with Notebooks

Now we shift our discussion from user perception to user behavior. Participants’ workflow in the Notebook condition was very similar to prior findings, e.g. [48]. They went through data exploration, feature generation, model building, hyperparameter tuning, and modeling selection steps. As this is a lab study centered around model building, participants were not asked to perform deployment steps of the model.

About the time-related features, as aforementioned, participants spent 15 minutes (SD = 6.8) in generating the first model (BN2). Note that this BN2 measure also includes the time participants spent in pre-processing and splitting data (BN1 9.4 minutes, SD = 5.5),

*In our study, the dataset was simple, so it took AutoDS only a few minutes to get the first model generated, with a more complicated dataset (e.g., hundreds of MB data file), this training step could take hours.*
so the actual model building task does not take that long. A few participants (N = 2) were marked “un-successful” as they did not perform the necessary data splitting step (F1).

In investigating the dataset, seven participants (47%) performed some form of exploratory data analysis, either by looking at tables that summarized descriptive statistics of the data, or by producing graphs and charts (BN4). But none of the participants wrote new code to explore the data distribution or generate visualizations to support their findings. From the post-study interview, almost all participants mentioned that if they had had more time, they would have loved to conduct more data exploration and understanding of the domain, and consulting with domain experts. By doing so, they believe they could have built better models, and increased their confidence in the model they generated.

“... I need to talk with domain experts or doctors to understand the data and feature ... whether my current model makes sense. Then, I need to think about how to create new features to improve the model.” (P29, M, Notebook)

Only four participants (27%) performed some form of feature engineering, by transforming, scaling, or combining existing features to create new features (BN5). Some argued that they did not have time, while a few others stated they did not do so for this simple, small dataset.

“I know SVM’s and Random Forest, in problems like this you don’t need to pre-normalize [the data]. RF can handle it.” (P28, M, Notebook)

About the quantity of the outcome, Notebook participants tried on average 3.13 (SD = 1.69) models (BN3). Three participants focused all of their attention on just one model, and four participants tried all five suggested models. Despite finishing the task minutes early, participants who finished only one model argued they did not have enough time to try more models, or so they believed. All of the participants used only the recommended models in the Notebook skeleton, with them justifying:

“I would [still] try KNN, RF, Logistic Regression [without your recommendation], because it’s a simple binary classification.” (P18, M, Notebook)

In summary, the results from the Notebook condition are not surprising. Data scientists followed the general pattern of data science workflow, as reported previously. This is a good result for us, as it means that we have successfully replicated data scientists’ day-to-day data science jobs in the lab environment. And by tracking various behavioral and perceptual measures, we now have a solid baseline condition to compare with data scientists’ new ways of working with AutoDS.

5.5 Human-Crafted Models v.s. AutoDS-Built Models

We use this section to delve deeply into the comparison of the two ways of working for data scientists in building models. We start with various comparison analyses [46] on the behavioral patterns from participants, the outcomes of the task, and finally participant attitudes.

5.5.1 AutoDS Creates More Models Faster and With Fewer Errors.

AutoDS easily generated 8 models with various algorithm and hyperparameter combinations, whereas participants in Notebook condition generated 3.13 (SD = 1.69) models (BN3). To provide a fair comparison, participants in AutoDS examined in detail 3.8 (SD = 1.2) models out of the 8 models (BA6), which served as a candidate set for participants to select the final model. That count (BA6) is still a bit higher than those in Notebook condition (BN3), though the t-test shows the difference is not significant (BA6, t(28) = 1.25, p = .223).

About the accuracy of the final selected model, we first reiterate that 7 participants in the Notebook condition reported either an accuracy score other than the ROC AUC metric, or reported the score from the same training data set; as a result, their scores can not be considered valid model scores. We conducted an analysis of variance (ANOVA) to compare the ROC AUC scores (B1) between participants with AutoDS and only the successful Notebook participants. When reporting ANOVA results, we included effect size as partial $\eta^2$, which is the proportion of variance accounted for by each factor in the model, controlling for all other factors. To interpret effect sizes, Miles & Shevlin [47] gives guidance that partial $\eta^2 \geq .14$ is a large effect, $\geq .06$ is a medium-sized effect, and $\geq .01$ is a small effect. For participants in AutoDS condition generated and selected the final model with higher ROC AUC scores (.919 SD=.01) than participants with Notebooks (.899 SD=.02), F[1, 21] = 7.61, $p = .01$, partial $\eta^2 = .27$. (B1)

As aforementioned, participants spent much more time in creating models in Notebook condition than in AutoDS condition. Even if we compare the time participants spent on the first model in Notebook (time to first model 15.0 SD=6.8 min) (BN2) v.s. the time they generate 8 models in the AutoDS condition (config + run time 4.3 SD=1.0 min) (BA1+BA2), that difference is significant $t(14.7) = 6.0$, $p < .001$. One factor that contributes to this time difference is that participants in the Notebook condition spent a significantly greater amount of time searching for SK-learn library documentation on the web (6.4 SD=2.6 min) than participants in the AutoDS condition (0.93 SD=1.4) (B3). $t(21.3) = 7.2$, $p < .001$.

Given that participants had limited time in this study, we found that many Notebook participants stopped when they felt they had created a “good enough” model and the amount of time they needed to continue to refine their model (e.g. by doing feature engineering) was more than the remaining amount of time in the study. Participants with AutoDS had an easier time understanding which model had the highest accuracy, but spent much of their time trying to understand why. They leveraged the generated code to interpret the decisions that AutoDS made in the process (BA7), and to evaluate the legitimacy of the AutoDS system. After modifying a couple hyperparameters of the model and seeing the expected changes in accuracy score (BA8), one participant believed they understood why AutoDS selected that particular set of hyperparameters and decided:

“Ok, I get an explanation and break down as to what decisions it made, I’ll tweak the cross validation then.” (P4, F, AutoDS)

5.5.2 Factors That Led to More Accurate Models in AutoDS Condition. To understand what factors led to participants choosing a
more accurate model while working with AutoDS, we created a regression model to predict ROC AUC scores in AutoDS condition (B1). We included a variety of behavioral measures (B3, BA1, BA3, BA4, BA6, BA7, BA8)\(^5\) and three self-reported background measures of data scientists (P1, P2, A1) to control for expertise effects: years practicing data science, prior experience with scikit-learn experience, and prior experience with AutoDS. We also control how long the participants took to complete the task. For AutoDS participants, we found a number of significant predictors of ROC AUC score, detailed in Table 2.

We found that the longer participants searched online for documentation and task-related information in the AutoDS condition (B3), the lower their accuracy score was in the selected model. We observed a similar trend in the Notebook condition, where the more experienced data scientists seemed to spend less time in searching for documentation.

The longer participants spent in examining the leaderboard and the pipeline details, the better the model they obtained (BA3, BA4). This suggests that the more time and effort participants dedicated to understanding the AutoDS model results, the better their outcome. There were quite a few models generated by AutoDS, and participants only needed to inspect a number of them in detail (BA6). They may have been interested in viewing the pipeline’s code in Notebook as well (BA7). Both behaviors led to higher accuracy in the model they selected.

The behavior of changing pipeline code did not necessarily increase the accuracy score (BA8), partially because participants changed the code to make sure they could see corresponding changes in model score, even if the score went down. That gave participants reassurance of the AutoDS generated models.

5.5.3 Confidence in Human-Crafted Models. Other than the accuracy score of the final model, we also collected how confident each participant was in their final selected model (A4) at the end of the study. Overall ratings of confidence landed in the middle of the scale (2.9 SD=.97 out of 5), suggesting that participants felt they could have produced even better models if they had had more time.

Participants in AutoDS condition were significantly less confident (2.4 SD=.98) in their models than participants in the Notebook condition (3.3 SD=.72), \(t(25.7) = -2.9, p < .01\). An important consideration here is that more confidence did not equate to better models between the two conditions. This may suggest that while the AutoDS users had more options to compare and study, their counterparts in the Notebook condition were invested in writing code from the start. This investment of time and effort into a model could influence users’ perspectives when it came to how confident they were. This is backed by the qualitative interview:

“It’s very confident that this is the best model I can get with this dataset in 30 mins” (P18, M, Notebook)

5.5.4 Trust of AutoDS Increases After Use. To form a deeper understanding of people’s trust in AutoDS, we decomposed the trust into various fine-grain dimensions. We asked AutoDS condition participants to complete an survey developed by Hoffman et al. [27] at the end of the study (AA5). The survey was intended to evaluate trust in Explainable AI systems (XAI), and contains 8-items, each with 5-point Likert scale responses ranging from Strongly Disagree to Strongly Agree (Table 3). Factor analysis indicated that removing item Q2 increased reliability of the scale, so we aggregated the final scale by omitting this item.

Q1. I am confident in the AutoDS. I feel that it works well.
Q2. The outputs of the AutoDS are very predictable.
Q3. The AutoDS is very reliable. I can count on it to be correct all the time.
Q4. I feel safe that when I rely on the [AutoDS] I will get the right answers.
Q5. AutoDS is efficient in that it works very quickly.
Q6. I am wary of the AutoDS.
Q7. AutoDS can perform the task better than a novice human user.
Q8. I like using the system for decision making.

Table 3: XAI survey from [27]. With the removal of Q2, this scale has acceptable reliability (Cronbach’s $\alpha = .75$).

Previous literature [27] suggests to use the XAI scales as an overall score. The overall XAI score was quite positive (3.6 SD=.41 out of 5) (AA5). Participants found the AutoDS efficient, predictable, and liked it for decision making.

| Factor                                                                 | M     | SD    | t     | p     | partial $\eta^2$ | Direction |
|-----------------------------------------------------------------------|-------|-------|-------|-------|------------------|-----------|
| Years spent practicing data science (P1)                              | 3.5   | 2.7   | .955  | n.s.  | .47              | +         |
| Prior experience with scikit-learn (P2)†                               | 3.6   | 1.1   | .798  | n.s.  | .43              | +         |
| Prior experience with AutoDS (A1)†                                    | 1.7   | .81   | -0.55 | n.s.  | .28              | -         |
| Time on task**                                                         | 29.0  | 3.6   | 6.96  | .006  | .73              | +         |
| Time spent searching for information (B3)*                             | .95   | 1.4   | -3.19 | .05   | .77              | -         |
| Time configuring AutoDS (BA1)                                         | 2.3   | .96   | 2.17  | n.s.  | .01              | +         |
| Time examining the leaderboard (BA3)*                                 | 9.7   | 3.4   | 5.1   | .04   | .27              | +         |
| Time examining pipeline details (BA4)*                                | 3.9   | 2.2   | 4.34  | .02   | .15              | +         |
| Number of pipelines examined (BA6)**                                  | 3.8   | 1.2   | 7.89  | .004  | .93              | +         |
| Number of pipeline’s code inspected (BA7)**                           | 2.3   | .70   | 5.33  | .01   | .87              | +         |
| Number of pipeline’s code edited (BA8)                                | .8    | .94   | -1.26 | n.s.  | .65              | -         |

\(\text{Table 2: Factors that predicted higher ROC AUC scores for AutoDS participants. Model adjusted } R^2 = .85, (\text{ and } **) \text{ Indicates effects that are both significant } (p \leq .05, \leq .01) \text{ and sizable } (\text{partial } \eta^2 \geq .06). (\text{†}) \text{ Prior experience with scikit-learn and AutoDS were rated on a 5-point scale (1=low, 5=high).}\)
“It’s fast and it gives you visualisations to compare the models, this saves me a lot of time” (P8, M, AutoDS)

However, participants wondered about the reliability of AutoDS, trying to understand the rationale behind AutoDS’s decisions.

“I’m not sure about the features it created for me” (P5, M, AutoDS), “It selected in one case random forest and in another logistic regression, but why, can i choose the classifier?” (P6, F, AutoDS)

In order to gauge how participants felt about AutoDS after having used it, we measured their attitude toward AutoDS twice, once at the beginning of the study (A2, A3) and once at the end (AA2, AA3). Participants’ opinions generally did shift in a positive direction after experiencing AutoDS. Participants had significantly higher levels of trust in AutoDS after using it (3.5 SD=.74) than before (2.7 SD=1.1), t(24.4) = −2.3, p = .03. This finding is consistent with the finding that all 15 participants reported that they want to adopt AutoDS in their day-to-day model building work after the experiment. As to whether our participants felt that AutoDS would one day replace data scientists, there was a small shift in opinion toward feeling that it would, but it still falls in the negative direction, and this difference was not significant (A3) (pre-study 2.4 SD=.83, post-study 2.9 SD=1.2, t(25.3) = −1.4, p = n.s.).

6 DISCUSSION
Motivated by literature, we began the investigation on how data scientists use an AutoDS system in DS tasks. Through our analyses, we found that participants working with AutoDS not only can create more models and faster, but more importantly these models are at a higher accuracy and with fewer human-errors, comparing to participants working with a Jupyter Notebook coding environment. With AutoDS’s help, data scientists can afford to spend more time in understanding the results and inspecting the codes generated by AutoDS, whereas in the baseline condition participants had to spend lots of their efforts and time in searching for library documentations and writing code from scratch. However, despite participants acknowledge all these benefits from using AutoDS, participants still trust their manually-crafted models more than the AutoDS generated model. These results suggest design improvement for AutoDS technology, and enlighten us about the future of human-centered automated data science work.

6.1 Design Implications
Our results suggested that AutoDS prototype’s code generation feature, which automatically translate a resulting model into human-readable Python code, is very welcomed by the participants. They could inspect the codes to see the decisions made by AutoDS. They can rationalize some of those decisions, and they could even change the code and see if that changes the result as expected. Furthermore, we observed there are a couple participants who kept working on the code generated by AutoDS to achieve a better model, that use case again supports our claim that data scientists and AutoDS together could deliver better results. Other than the possible use of the entire code, data scientists could also easily migrate or replicate a segment of the generated code, maybe with a transformation function, some hyperparameters, or other decisions made by AutoDS into a different task and context. Thus, we highly recommend AutoDS systems to provide such code-generation feature.

We also learned that participants have trouble in trusting AutoDS system, and they have more confidence in their worse-performing manually-created models than in the higher quality AutoDS-generated models, thus the explainable and trustworthy AutoDS research agenda should be prioritized. The fact that people loved the code-generation feature could also attribute to the needs of a transparent and trusted AutoDS. Participants wanted to understand not only what the decisions are (code-generation satisfied that), but also why AutoDS made such decisions. However, only the generated code for the result model was not enough. We need to design AutoDS systems to provide better explanation for why certain decisions were made. For example, when showing users the top performed algorithm and the optimized set of hyperparameter values, we could also reveal the information about all the other candidates considered, and why AutoDS eliminated those options. Another example is that for the new features engineered by AutoDS, users should have a better view of how those features are generated and chosen in the middle of the feature engineering process, because users may have some domain knowledge to prevent the nonsense transformations (e.g., absolute value of gender). We are glad to see that recently there are some researchers moving toward this direction [13]. We should also caution readers that we are not arguing to show a user all the information AutoDS has. Full transparency causes information overload and is no better than no transparency. This links back to a well-established CSCW theory: “social translucent” [15], where researchers argue to show the information at the right moment and at the right level of details, and we should learn from our past.

6.2 Human-Centered Automated Data Science
Our result showed that some participants worked over a wider range of AutoDS results, some others focused on improving the code of one particular model (BN6 and BA7). The more successful participants were the ones who tried a wider range of approaches rather than focusing all of their attention on just one model. This finding echoed wisdom in the artistic domain, where the most creative works emerge when favoring quantity over quality [4]. And this was not isolated that the data science work appears linked to a well-established CSCW theory: “social translucent” [15], where researchers argue to show the information at the right moment and at the right level of details, and we should learn from our past.
They hand over information to each other and share responsibility. Together, AutoDS plays a partner role in the future of human-centered automated data science practice.

We believe AutoDS technologies will become available to more and more data scientists, allowing them a chance to craft models together with AI. We agree with the majority of our participants that AutoDS will not replace data scientists’ job. Instead, a human-centered AutoDS will play a more important assistant role to the human data scientists in new paradigm of data scientist’s work.

In this new paradigm, data scientists’ role will shift, as suggested by our findings: they can spend less time in the tedious model training and hyperparameter tuning tasks, but spend more time in understanding the data, communicating with the domain experts, and selecting the model to best fit the domain and context. In addition, they will need to spend a big proportion of their time to rationalize the AutoDS decisions and results, and translate those decisions to present to other human stakeholders.

In this new paradigm, not only professional data scientists but also end-customers and domain experts can also build ML solutions to answer their own simple questions with their data. Our system provide a GUI and an automatically export human-readable notebook in automatically models building. The future in which various human stakeholders can work together with AutoDS is promising, but there are works needed to be done to achieve that vision. This work is just the first step.

6.3 Limitations

We acknowledge our works limitations as follows: this is a lab experiment study, thus it has the common limitations as any other lab experiments [17]. For example, in the Notebook Condition, we provided participants a code skeleton, which may also bias their behaviors in that condition. Another example is that the task and data set is tailored as simple and specific tasks to emphasize model building, thus the reported behaviors of participants interacting with AutoDS may be different from when they actually adopt AutoDS in their daily DS projects. In an actual data science project, data acquisition and curation are more significant problems for data scientists during the ML lifecycle. The AutoDS system presented in this paper is just the starting point of a long-term project. We have another paper in submission that discusses human-AI collaboration in automated data preparation and curation process. In that work, we used reinforcement learning instead of AutoML, because it is better suited for the task.

Another limitation is that all the participants are professional data scientists coming from a technology company, there may be some selection bias in their background. For example, on average, they rated themselves as moderate level of data science expertise. This participant population may also impose limitations on the generalizability of our paper’s findings. We call out these external validity limitations to the reader who plan to apply the findings to other contexts.

7 CONCLUSION

Our work presents an AutoDS prototype system, and a between-subject user experiment with with 30 professional data scientists to use the AutoDS system, or use python in notebooks, to complete a data science model building task. Grounded in the results, we present design implications for building AutoDS systems to better incorporate into human workflows. We also discuss future research directions for human-centered automated data science.

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