LEARNING TO ADVISE HUMANS BY LEVERAGING ALGORITHM DISCRETION

Nicholas Wolczynski
University of Texas at Austin
nicholas@mccombs.utexas.edu

Maytal Saar-Tsechansky *
University of Texas at Austin
maytal@mail.utexas.edu

Tong Wang *
University of Iowa
tong-wang@uiowa.edu

ABSTRACT
Expert decision-makers (DMs) in high-stakes AI-aDvise d Team (AIDeT) settings receive and reconcile recommendations from AI systems before making their final decisions. We identify distinct properties of these settings which are key to developing AIDeT models that effectively benefit team performance. First, DMs in AIDeT settings exhibit algorithm discretion behavior (ADB), i.e., an idiosyncratic tendency to imperfectly accept or reject algorithmic recommendations for any given decision task. Second, DMs incur contradiction costs from exerting decision-making resources (e.g., time and effort) when reconciling AI recommendations that contradict their own judgment. Third, the human’s imperfect discretion and reconciliation costs introduce the need for the AI to offer advice selectively. We refer to the task of developing AI to advise humans in AIDeT settings as learning to advise and we address this task by first introducing the AIDeT-Learning Framework. Additionally, we argue that leveraging the human partner’s ADB is key to maximizing the AIDeT’s decision accuracy while regularizing for contradiction costs. Finally, we instantiate our framework to develop TeamRules (TR): an algorithm that produces rule-based models and recommendations for AIDeT settings. TR is optimized to selectively advise a human and to trade-off contradiction costs and team accuracy for a given environment by leveraging the human partner’s ADB. Evaluations on synthetic and real-world benchmark datasets with a variety of simulated human accuracy and discretion behaviors show that TR robustly improves the team’s objective across settings over interpretable, rule-based alternatives.

1 Introduction

Advances in machine learning model performance and interpretability across domains have brought about a growing focus on human-AI (HAI) systems to enhance human decision-making (Cai et al., 2019; Soares and Angelov, 2019; Green and Chen, 2021; Basu et al., 2021; Lebovitz, Lifshitz-Assaf, and Levina, 2022). Most prior work that developed AI methods for human-AI teams focused on low-stakes settings where the AI can either make all decisions autonomously, or can decide to defer to the human for some tasks. In this work, we consider the task of learning to advise in high-stakes AI-aDvised Team (AIDeT) settings where the human must act as the final decision-maker (DM) for all instances. In such settings, the AI does not undertake any decisions autonomously and thereby does not decide whether to defer to the human; rather, the AI may only advise the human on some or all instances.

We account for fundamental properties of AIDeT contexts that significantly affect team performance. First, human DMs exhibit imperfect algorithm discretion behavior (ADB). Bansal et al. (2021a) demonstrate that AI ought to be optimized for team generalization performance in AIDeT settings characterized by human DMs who optimally reconcile algorithmic recommendations. However, prior work has established that humans’ discretion to accept algorithmic recommendations is not always optimal, to the detriment of the team (Dietvorst, Simmons, and Massey, 2015; Chiang...
and Yin [2021], Bansal et al. [2021b], Zhang, Lee, and Carter [2022]. We propose an AIDeT approach that learns to productively and reliably advise a human who may exhibit imperfect ADB.

Additionally, prior work that closely studied experts advised by AI highlighted the costs experts incur from exerting time and effort to reconcile AI recommendations that contradict their own initial judgment (Lebovitz, Lifshitz-Assaf, and Levina [2022]). Because experts’ resources are limited and costly, AIDeT systems ought to account for the costs of reconciling contradicting recommendations, which we refer to as contradiction costs going forward for brevity. Prior work which focused on the development of predictive models for HAI teams often assumed humans incur costs when the AI does not take action; yet, the high-stakes DM must always make (and is often liable for) the decisions, and only incurs additional costs when the AI takes action and provides a contradicting recommendation. Given humans incur contradiction costs and exhibit imperfect ADB, it is productive for an AIDeT system to make recommendations selectively, such as when the AI is likely more accurate and when the outcome of the human’s reconciliation is expected to justify the added contradiction cost. Therefore, learning how to advise selectively is an integral goal in this work.

Finally, prior work has established how the success of AIDeTs also hinges on AI recommendations that are inherently interpretable (Vellido [2020], Chiang and Yin [2021]). Rule-based models are widely recognized as one of the most intuitively understandable models for their transparent inner structures and good model expressivity (Rudin [2019]). Additionally, AIDeT systems yield more productive outcomes when experts can directly edit the patterns underlying the recommendations, so as to reflect the knowledge that the AI cannot otherwise learn (Caruana et al., 2015; Balagopal et al., 2021; Wang et al., 2022). Consequently, in this work, we provide an inherently interpretable, rule-based approach.

We comprehensively address the challenge of learning to advise by proposing a framework and an algorithm that satisfies all of the properties mentioned above to benefit high-stakes AIDeTs. Specifically, we make the following contributions:

• We identify and consider key properties of high-stakes AIDeT settings where an imperfect human DM may be advised by an AI but always undertakes the final decision. The human DM (1) can exhibit imperfect ADB towards the AI’s advice, (2) incurs costs from reconciling contradicting algorithmic recommendations and (3) benefits from interpretable recommendations.

• We theoretically motivate and develop a framework for learning to advise humans in high-stakes AIDeT settings.

• We develop the TeamRules (TR) algorithm which generates an inherently interpretable rule-based model designed to selectively advise a human DM. TR leverages the human partner’s decision history and ADB to learn how to selectively provide recommendations which minimize team loss defined in terms of (1) team decision error and (2) contradiction costs.

We evaluate TR’s performance relative to alternative rule-based methods on two synthetic and three real-world datasets when paired with a variety of simulated human behaviors. Our results show that TR reliably and effectively leverages the human’s ADB to selectively provide recommendations which improve the team’s objective over alternatives. Additionally, TR can adapt to the partner’s tolerance for added contradiction costs by exchanging improvements to team decision accuracy for lower total contradiction costs. We empirically demonstrate that the existing benchmarks represent a lower bound of performance as contradiction costs become prohibitive and as the accuracy of the model of the human’s ADB diminishes, showcasing the robustness of our method.

2 Related Work

2.1 Human-AI Teams

Existing literature on human-AI (HAI) teams is broad and considers a variety of perspectives and applications. HAI teams are increasingly deployed for decision-making in a multitude of high-stakes settings, including medicine (Cai et al., 2019; Balagopal et al., 2021) and criminal justice (Soares and Angelov, 2019).

Prior work on HAI teams demonstrated that directly optimizing the team’s objectives is key to producing AI systems which complement human DMs (Madras, Pitassi, and Zemel [2018], Bansal et al., 2021a). Specifically, Bansal et al. (2021a) consider a setting in which a DM exhibits optimal algorithm discretion behavior and show, in this setting, that AI can be optimized for team performance by considering the DM’s expected final decision within the model’s
training objective. However, humans’ discretion of algorithmic recommendations is not always optimal (Chiang and Yin, 2021; Dietvorst, Simmons, and Massey, 2015; Castelo, Bos, and Lehmann, 2019). We build on the work in Bansal et al. (2021a) in several ways: (1) we propose an approach that produces inherently interpretable recommendations, (2) we do not assume the human optimally reconciles algorithmic recommendations, (3) our method provides selective recommendations and thus can choose to withhold recommendations for some instances, and (4) we consider costs incurred by decision makers when they reconcile contradicting recommendations (Lebovitz, Lifshitz-Assaf, and Levina, 2022). Because we consider inherently interpretable rule-based recommendations, our methods are part of a different class of machine learning (ML) models than those considered in Bansal et al. (2021a) and our methods are not directly comparable. However, we show that our TR algorithm consistently exhibits superior empirical test performance when compared to models of the same class that were optimized for standalone AI decision accuracy, a result not yet established in Bansal et al. (2021a).

The AIDeT setting is distinct from the HAI team setting in which the AI system can make decisions autonomously without human involvement, but may defer to the human on some decisions (Madras, Pitassi, and Zemel, 2018; Wang and Saar-Tsechansky, 2020; Wilder, Horvitz, and Kamar, 2021; Keswani, Lease, and Kenthapadi, 2021; Gao et al., 2021; Bondi et al., 2022). Methods developed for the deferral setting need not address the human’s discretion behavior and contradiction costs to improve or evaluate the team’s performance.

Finally, our AIDeT setting is distinct from the sequential and online decision-making settings in which either the AI agent adapts to the human or the human and AI agent collaborate on a sequence of decisions in which either may act as an autonomous DM (Bordt and Von Luxburg, 2022; Biyik et al., 2022).

2.2 Algorithm Discretion

The term algorithm aversion was proposed to characterize humans’ tendency to avoid relying on an algorithmic recommendation in favor of human judgment, even when the algorithm’s performance is superior (Dietvorst, Simmons, and Massey, 2015; Castelo, Bos, and Lehmann, 2019). However, a human’s reconciliation of algorithmic recommendations can also exhibit over-reliance on these recommendations (Logg, Minson, and Moore, 2019; Mahmud et al., 2022), or be based on adequate judgment of relevant factors (Kim, Yang, and Zhang, 2020; Jussupow, Benbasat, and Heinzl, 2020). Consequently, in this work, the term algorithm discretion refers to the human’s arbitrary pattern to accept or reject algorithmic recommendations for any given decision instance. Our method models and aims to leverage any algorithm discretion behavior to improve human-AI team performance.

2.3 Rule-Based Models

Rule-based models are inherently interpretable and easy to understand because they take the form of sparse decision lists, consisting of a series of if... then statements (Yildiz, 2014; Rudin, 2019; Wang et al., 2021). This model form offers an inherent reason for every prediction-based recommendation (Letham et al., 2015). In many high-stakes domains, experts require interpretability to vet on the reasoning underlying the model’s predictions (Caruana et al., 2015). Furthermore, DMs are more likely to collaborate productively with an AI advising system if it produces inherently interpretable models that can be edited by the DM (Caruana et al., 2015; Balagopal et al., 2021; Wang et al., 2022).

The method we introduce in this paper builds on the H+RS method (Wang, 2019) originally proposed to offer partial interpretability for black-box models. H+RS is itself an extension of the Bayesian Rule Sets (BRS) method (Wang et al., 2017) for creating decision list classifiers. While these works do not consider the problem of advising a human, we adapted the H+RS and BRS methods as benchmarks to evaluate the benefits of leveraging ADB within a class of methods.

3 Leveraging Algorithm Discretion Behavior

We propose the AIDeT-Learning Framework, shown in Figure 1. This framework provides a concrete series of steps that can be implemented in practice to develop HAI-team models which leverage ADB to benefit decision-making in AIdeT settings. We first provide theoretical motivation for the potential benefits of leveraging ADB and follow with a detailed explanation of the steps in the AIDeT-learning framework.

3.1 Theoretical Motivation

We provide theoretical motivation for the potential benefits of leveraging ADB to improve team performance defined by an arbitrary loss function. Let $X$ be the set of possible examples with labels $Y = \{0, 1\}$, where $X \times Y \sim D$. We define a human’s ADB as their tendency to accept or reject algorithmic recommendations for arbitrary decision instances and feature values thereof. For simplicity of the exposition, we assume that the human’s ADB for a given instance is
deterministic. The space can be partitioned into \( \mathcal{X} = \mathcal{X}_A \cup \mathcal{X}_R \), depending on the human’s materialized algorithm discretion behavior (ADB). \( x_i \) is in \( \mathcal{X}_A \) if the human accepts a recommendation, meaning they update their initial decision \( h_i \) to recommendation \( \hat{y}_i \); similarly, \( x_i \) is in \( \mathcal{X}_R \) if the human rejects the AI recommendation and does not update their initial decision. Consequently, we have \( \mathcal{X}_A \times \mathcal{Y} \sim D_A \), and \( \mathcal{X}_R \times \mathcal{Y} \sim D_R \).

The overarching goal of our machine learning task is to learn a classifier \( c^* : \mathcal{X} \rightarrow \mathcal{Y} \), where \( c^* \in \mathcal{C} \) is selected by minimizing the expected loss \( L(y, c(x)) \) as follows:

\[
c^* = \min_{c \in \mathcal{C}} \mathbb{E}_{x,y \sim D}(L(y, c(x))).
\]

The expected loss can be partitioned as follows:

\[
c^* = \min_{c \in \mathcal{C}} \mathbb{E}_{x,y \sim D_A}(L(y, c(x))) + \mathbb{E}_{x,y \sim D_R}(L(y, c(x))).
\]

However, note that in our team setting, recommendations \( c(x) \) for instances drawn from \( D_R \) are rejected by the human. Thus, the expected loss from rejected recommendations is a function of \( h \) and is independent of \( c(x) \), and thus given by: \( \mathbb{E}_{x,y \sim D_R}(L(y, h)) \). The overall expected team’s loss we thus aim to minimize is:

\[
E_{x,y \sim D_A}(L(y, c(x))) + E_{x,y \sim D_R}(L(y, h))
\]

Given the human’s ADB, it is possible to obtain a superior classifier \( c' \in \mathcal{C} \) by solving for the following:

\[
c' = \min_{c \in \mathcal{C}} \mathbb{E}_{x,y \sim D_A}(L(y, c(x))).
\]

Because \( c' \) is directly minimizing loss over \( D_A \), then:

\[
E_{x,y \sim D_A}(L(y, c'(x))) \leq E_{x,y \sim D_A}(L(y, c^*(x))).
\]

This inequality theoretically justifies why considering humans’ ADB in training can benefit team performance. In practice, however, the human partner’s ADB is unknown, which poses a challenge to identifying \( D_A \) and \( D_R \). Rather than explicitly identifying \( D_A \) and \( D_R \), we can model the human partner’s discretion behavior with \( \hat{p}(a|x) \). In Appendix A we show how, assuming \( \hat{p}(a|x) \) is accurate, we can equivalently learn \( c' \) by minimizing the following:

\[
c' = \min_{c \in \mathcal{C}} \mathbb{E}_{x,y \sim D}(\hat{p}(a|x) \cdot L(y, c(x))).
\]

By leveraging the estimated discretion model \( \hat{p}(a|x) \), we can train \( c' \) on the entire set of data drawn from \( D \) rather than creating an explicit partition. As the accuracy of the discretion model decreases, Eq. 5 and Eq. 6 may no longer hold. We empirically assess the impact of low accuracy discretion models in our experiments.

3.2 AI-Advised Team (AIDeT)-Learning Framework

Our AIDeT-learning framework consists of three phases. The Human Interaction Phase serves to model the human partner’s decisions and ADB. Given training data \( \{X, Y\} \), we conduct two tasks involving the human. First, either historical data of the human’s past decisions is obtained, or, in the absence of such history, the human records their
decisions for a set of training instances; We refer to the resulting vector of the human’s decisions as $h$. The second task involves recording the human’s ADB. One simple way is to provide AI recommendations to the human partner for a subset of training instances, $X_d$, and record the human’s decision when the AI makes a contradictory recommendation, thereby producing a binary vector $a_d$. In the Discretion Learning Phase, we learn a discretion model of the human’s ADB, $\hat{p}(a|x)$, from data $\{X_d, a_d\}$, to infer the discretion outcome, i.e., whether the human will accept or reject the AI’s recommendation for a given instance. For brevity, we denote $p(a|x)$ and $\hat{p}(a|x)$ as $p(a)$ and $\hat{p}(a)$, respectively, going forward. We leave the focus of developing superior discretion recording and model training processes to future work. For the remainder of the paper, we assume that a reasonable discretion model can be learned and we evaluate our method’s performance with discretion models of varying quality.

Finally, given data $D = \{X, Y, h, \hat{p}(a)\}$ acquired in the previous steps, we proceed to the Decision Task Learning Phase during which we train an HAI team model $p(y|x, h, \hat{p}(a))$ that leverages a discretion model and human decision history to optimize the HAI team’s performance. This entails defining team performance in terms of an objective and relevant metrics, depending on the decision-making context. Next, we develop an algorithm which leverages ADB to optimize for the desired objective.

## 4 The TeamRules Method

Here we develop our rule-based TeamRules (TR) model, which consists of a set of inherently interpretable rules. First, we formally define key terminology:

**Definition 1 (Rule).** A rule $r$ is a logical expression made of conditional statements about a subset of feature values. $r$ covers an example $x_i$, denoted as $C(r, x_i) = 1$, if the logical expression evaluates to true given $x_i$.

**Definition 2 (Rule Set).** A rule set $R$ is a collection of rules. $R$ covers an example $x_i$, denoted $C(R, x_i) = 1$ if at least one rule $r$ in $R$ evaluates to true given $x_i$.

For any given decision instance, TR provides a recommendation to the human if the instance is covered by its rule set, otherwise, TR does not advise the human on the corresponding decision instance. Consequently, TR simultaneously learns which recommendations to make and when to avoid making recommendations to benefit the team’s performance. Figure 2 illustrates the team’s decision process in deployment when TR is paired with a human to produce decisions. TR takes as input the set of augmented instances $D = \{x_i, y_i, h_i, \hat{p}(a_i)\}_{i=1}^n$, and then generates a set of positive and negative rules denoted $R^+$ and $R^-$, respectively. The set of positive and negative rules determines the model’s prediction $\hat{y}_i$ for instance $i$.

The TR decision-making process is specified as follows:

- **if** $C(R^+, x_i)$, then $\hat{y}_i = 1$
- **elif** $C(R^-, x_i)$, then $\hat{y}_i = 0$
- **else** provide no recommendation (use $h_i$)

Figure 2: TeamRules + Human Partner Decision Process in AI-advised Team (AIDeT) Setting
We evaluate the performance of our approach with the following experiment setup. We compare the performance of our algorithm with two baseline methods: a standard rule mining algorithm and a simple thresholding method. The baseline methods are evaluated on the same datasets used in our experiments. The results show that our approach significantly outperforms the baselines in terms of accuracy and efficiency. The full results and details can be found in Appendix B.
5.1 Experimental Setup

**Benchmarks** To our knowledge, no existing method leverages a human partner’s ADB and decision history to learn how to selectively advise a high-stakes DM with rule-based recommendations which maximize team decision accuracy and minimize contradiction costs. Consequently, we utilize the inherently interpretable rule-based Bayesian Rule Set (BRS) method, which does not leverage any human information (Wang et al., 2017), to assess whether TR yields better team performance than can be achieved by advising the human with rules optimized solely for predictive accuracy with no consideration of the human. In addition, we examine whether leveraging the human’s discretion model is advantageous for TR’s team performance by adapting the existing H\_R\_S rule-based method so that it optimizes the same objective as TR, utilizes the human’s decision history, and has the ability to selectively make recommendations, but does not leverage the human’s ADB. We adapt H\_R\_S by removing the interpretability and transparency optimization steps, and including a contradiction cost regularization term in the objective. We call this updated method c-H\_R\_S and show the full algorithm in Appendix D.

We compare all three methods in the AIDeT setting: the rule-based model makes recommendations and a human partner decides whether to accept the recommendation. To assess the value of leveraging a discretion model independently of the discretion model’s accuracy, we first assume perfect knowledge of the human’s ADB. We later assess TR’s performance as discretion model accuracy decreases.

**Datasets** We experiment on two synthetic and three real-world datasets. The first simulated dataset (named Checkers) is a 2-dimensional checkerboard example in which we limit the model capacity to a rule length of 1. This limit on model capacity is set to create an exaggerated scenario in which it is impossible for any model in this class to get higher than 50% accuracy without leveraging additional human information. The second dataset (named Gaussian) is a more complex, 20-dimensional dataset in which the true underlying classification mapping is a complex function of all features. The synthetic datasets allow for clear analysis of results in a controlled environment. We also utilize real-world decision-making datasets: the Adult dataset from the UCI Machine Learning Repository (Dua and Graff, 2017), FICO dataset from the explainable machine learning challenge (FICO, 2018), and HR employee attrition dataset from Kaggle.\(^3\) We limit the model capacity for these datasets to a rule length of 3, ensuring all models remain easy to interpret by a DM and are compared under the same capacity limits.

**Simulating Human Algorithm Discretion Behavior** We evaluate our method’s performance under a variety of human behaviors. We first simulate human decision history such that the human has varying decision accuracy across instances by partitioning the data into high and low human accuracy regions using an arbitrary function of all available features. In addition, we evaluate TR for three different simulated human ADBs: Rational, Neutral, and Irrational. A rational DM knows their relative decision accuracy for different instances, and accepts recommendations in the region in which they have low accuracy while rejecting in the region they have high accuracy. An irrational DM does the opposite: they irrationally reject recommendations when they have low accuracy and accept recommendations when they have high accuracy. Lastly, we simulate a neutral human DM who is often, but not always, rational. The neutral human behavior may better reflect human experts, as humans rarely exhibit either perfectly rational or irrational discretion (Johnson, 2021). We simulate the neutral human behavior such that most, but not all, of the instances the human accepts recommendations for are instances in the human’s low accuracy region. The neutral human also accepts recommendations for some instances in their high accuracy region. Given the above behavior, the human exhibits deterministic ADB to accept or reject recommendations. A stochastic behavior is likely in practice and primarily affects the predictive accuracy of the discretion model that predicts the human’s ADB, and thereby TR’s performance. We thus also evaluate our approach when the discretion model’s accuracy ranges between 0.5 – 1. We provide full details on our datasets and human behavior simulation procedures in Appendix E.

**Evaluation Metrics** Our primary goal is to evaluate the Total Team Loss (TTL) on the test set $\tilde{D}$. TTL includes the team’s decision loss and the loss from incurred contradiction costs. The team’s decision loss (TDL) on test data $\tilde{D}$ is given by: $TDL = \sum_{i \in \tilde{D}} \|y_i - \hat{y}_i\|/N_{\tilde{D}}$. The total contradiction loss (CL) is given by: $CL = \alpha \sum_{i \in \tilde{D}} \|y_i - h_i\|/N_{\tilde{D}}$, where $\alpha$ is the cost of reconciling a single contradicting recommendation. Finally, we define the total team loss (TTL) as: $TTL = TDL + CL$.

5.2 Results

We state key questions followed by discussion on the experiments and results which address them.

\(^3\)https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset
We now focus on the plots on the right of Figure’s 3a,b,c that show the team decision loss (TDL) vs. the number of contradictions. When contradiction costs are low, there are more opportunities to benefit the team by selectively advising the human. As contradiction costs rise, the value of providing contradicting advice to the human to correct them decreases. Consequently, both TR and BRS demonstrate that when the DM is rational, contradictions. In Figure 3a, we see that TR exploits these opportunities more effectively than c-HvRS when contradiction costs are low. As contradiction costs rise, the value of providing contradicting advice to the human to correct them decreases. Consequently, both methods make fewer recommendations, and the total team loss they each achieve approaches that of the human’s ADB independently of the effects of the accuracy of the discretion model.

Results for the FICO dataset are shown in Figure 3 and all other results are consistent and shown in Appendix F. The contradiction costs from 0 to 1. Given BRS only aims to increase the recommendations’ accuracy and cannot account for contradiction costs, to make the comparison fair we set these costs to 0. We also first consider a perfect estimate of the human’s ADB to assess the potential benefits of TR’s leveraging of ADB independently of the effects of the accuracy of the discretion model. Results are shown in Table 1. For most datasets and settings, except for one, TR either outperforms or is equivalent to the best alternative(s). In the rational Adult dataset setting, BRS outperforms TR. Importantly, recall that in this setting, we ignore contradiction costs and assume the human is a perfect gatekeeper of recommendations; thus, TR can improve over BRS only if it both accurately assesses the human’s performance in the accept region and identifies rules that exceed BRS’s performance in this region. If, for example, TR’s estimation of the human’s decision performance in the accept region is not sufficiently accurate, then BRS’s naive strategy can yield better outcomes. Nevertheless, TR matches or improves on alternatives in all the practical settings where the human ADB is imperfect, and in all but one of the 15 total settings.

### 5.2.1 Does learning to advise using TR lead to lower total team loss?

Given BRS only aims to increase the recommendations’ accuracy and cannot account for contradiction costs, to make the comparison fair we set these costs to 0. We also first consider a perfect estimate of the human’s ADB to assess the potential benefits of TR’s leveraging of ADB independently of the effects of the accuracy of the discretion model. Results are shown in Table 1. For most datasets and settings, except for one, TR either outperforms or is equivalent to the best alternative(s). In the rational Adult dataset setting, BRS outperforms TR. Importantly, recall that in this setting, we ignore contradiction costs and assume the human is a perfect gatekeeper of recommendations; thus, TR can improve over BRS only if it both accurately assesses the human’s performance in the accept region and identifies rules that exceed BRS’s performance in this region. If, for example, TR’s estimation of the human’s decision performance in the accept region is not sufficiently accurate, then BRS’s naive strategy can yield better outcomes. Nevertheless, TR matches or improves on alternatives in all the practical settings where the human ADB is imperfect, and in all but one of the 15 total settings.

### 5.2.2 How does TR perform as contradiction costs vary?

Different environments are characterized by the human’s unique tolerance for incurring additional contradiction costs to improve the team’s decisions. We thus evaluate TR and c-HvRS for different degrees of tolerance by varying the contradiction costs from 0 to 1. BRS is excluded from this evaluation as it does not have a mechanism to account for incurred contradiction costs.

Results for the FICO dataset are shown in Figure 3 and all other results are consistent and shown in Appendix F. The plots on the left show Total Team Loss as a function of the contradiction cost. Lower contradiction costs indicate that correcting a human’s decision through advising is valued more than avoiding a contradiction; when the cost is 1, the value from correcting a decision is entirely offset by the additional contradiction cost incurred.

When contradiction costs are low, there are more opportunities to benefit the team by selectively advising the human. As shown, TR exploits these opportunities more effectively than c-HvRS when contradiction costs are low. As contradiction costs rise, the value of providing contradicting advice to the human to correct them decreases. Consequently, both methods make fewer recommendations, and the total team loss they each achieve approaches that of the human’s standalone decision accuracy.

### 5.2.3 How does TR improve team decisions over c-HvRS?

We now focus on the plots on the right of Figure’s 3a,b,c that show the team decision loss (TDL) vs. the number of contradictions. In Figure 3a, we see that TR is able to achieve a lower TDL by offering more contradictory advice. This demonstrates that when the DM is rational, TR is able to generate rule sets which more accurately cover instances that the human accepts recommendations for while also covering more of the instances the human would reject recommendations for. Thus, TR successfully leverages its understanding of the rational DM’s ADB to advise them
on their area of weakness by relying on them to reject advice in their area of strength. As the DM’s tolerance for contradictions decreases, TR is no longer able to rely on the human as effectively to reject instances in their area of strength due to greater incurred contradiction costs.

In Figure 3c, we can see that c-HyRS, without an understanding of the DM’s ADB, generates rules which would provide more benefit in the reject region than the accept region without realizing that attempting to correct the human on the reject region provides no benefit to the team. In contrast, we find that regardless of the human’s tolerance for contradictions, TR always learns not to provide advice to the irrational DM who already has perfect accuracy on the accept region.

Figure 3b corresponds to a DM that is uniquely neither perfectly rational or irrational. Given this behavior, TR is able to selectively provide recommendations which advise the human more accurately in the accept region while contradicting the human as often as c-HyRS.

Overall, the set of results in Figure 3 demonstrates how TR improves on team decision loss by selectively contradicting the human and leveraging ADB while also adapting to the human DM’s unique tolerance for contradictions.

Figure 3: Total team loss for varying contradiction costs. (Left) Total Team Loss vs. Contradiction Cost. Results show average and stdev (bar). (Right) TDL vs. Number of contradictions. Line connects averages for different cost settings. Transparent points show individual results for cost+run.
5.2.4 How robust is TR to inaccurate discretion models?

In real-world applications, we do not assume access to a perfectly accurate discretion model. In practice, ADB would be estimated via training a model on a small set of labeled data. In our final experiment, we investigate how the accuracy of $\hat{p}(a)$ impacts team performance and how much it can deteriorate before TR no longer provides value. We gradually decrease the accuracy of $\hat{p}(a)$ by adding random error while setting $\alpha = 0$ to assess how the accuracy of $\hat{p}(a)$ impacts TTL for TR. Results for the FICO dataset are shown in Figure 4 (results for Gaussian data are consistent and shown in Appendix F). We find that TR is robust to imperfect $\hat{p}(a)$ models with accuracy as low as 60% in some settings. TR is robust to imperfect $\hat{p}(a)$ models with accuracy of 70% in all settings for our experiments. Intuitively, small errors in $\hat{p}(a)$ cause TR to place a small weight on some instances in $D_R$. In practice, learning from a few out-of-distribution examples would not necessarily hurt the model. As the discretion model reaches 50% accuracy, TR randomly focuses on instances in $D_A$ and $D_R$, which provides a natural robustness mechanism as TR approaches c-HyRS by learning from the same distribution albeit with potentially less data considered. With a discretion model of lower than 50% accuracy, TR would prioritize instances in $D_R$, which could lead to worse team performance if $D_R$ were to differ greatly from $D_A$. However, in practice, discretion model accuracy can be evaluated and discretion models with 50% accuracy or lower should not be utilized.

6 Conclusion and Future Work

In this work, we identify key properties of AI which benefit AI systems’ ability to learn to advise humans in high-stakes AIDeT settings. We then introduce the AIDeT-Learning framework and instantiate it to develop the TR method which selectively provides inherently interpretable rule-based recommendations by leveraging the human partner’s ADB and accounting for the partner’s tolerance to reconciling contradicting recommendations. We show that our framework and method lead to improved team performance over relevant alternatives. We believe this work is an exciting first step toward the development of methods that learn to selectively advise humans in AIDeT settings and can be built upon to produce AI systems which provide greater benefit to expert DMs in high-stakes settings. Future research can build on our work by developing methods which effectively and efficiently infer ADB, by improving on how we optimize for the team’s objective and by further considering which objective’s best represent desired team outcomes, or by studying how expert decision maker’s interact with models which provide selective recommendations and leverage the human partner’s ADB to gain a better understanding of when such methods can provide the most benefit in practice.

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A Proof

Proof. Assuming an accurate discretion model in which \( \hat{p}(a|x) = 1 \) when \( x \in X_A \) and \( \hat{p}(a|x) = 0 \) when \( x \in X_R \).

Then:

\[
\begin{align*}
e' &= \min_{c \in C} \left[ \mathbb{E}_{x,y \sim D} (\hat{p}(a|x) \cdot L(y,c(x))] \right] \\
&= \min_{c \in C} \left[ \mathbb{E}_{x,y \sim D_A} (\hat{p}(a|x) \cdot L(y,c(x))) \\
&\quad + \mathbb{E}_{x,y \sim D_R} (\hat{p}(a|x) \cdot L(y,c(x))] \right] \\
&= \min_{c \in C} \left[ \mathbb{E}_{x,y \sim D_A} (1 \cdot L(y,c(x))) \\
&\quad + \mathbb{E}_{x,y \sim D_R} (0 \cdot L(y,c(x))] \right] \\
&= \min_{c \in C} \left[ \mathbb{E}_{x,y \sim D_A} (L(y,c(x))] \right] \\
\end{align*}
\]

\[
\begin{align*}
L(D,R) &= \ell(D,R) + \omega(D,R) \\
\ell(D,R) &= \sum_{i=1}^{n} \left[p(a_i) \left( ((1 - y_i)C(R^+, x_i)) \\
&\quad + (y_i(1 - C(R^+, x_i)))C(R^-, x_i) \\
&\quad + (1 - C(R^+, x_i))(1 - C(R^-, x_i)) \\
&\quad \times (y_i(1 - h_i) + h_i(1 - y_i)) \right] \\
\omega(D,R) &= \alpha \sum_{i=1}^{n} \left[ (1 - h_i)C(R^+, x_i)) \\
&\quad + (h_i(1 - C(R^+, x_i)))C(R^-, x_i) \right] \\
\end{align*}
\]

B Objective

The TR objective is set to the team loss function:

\[
L(D,R) = \ell(D,R) + \omega(D,R)
\]

Where \( \ell(D,R) \) is the discretion adjusted decision loss:

\[
\ell(D,R) = \sum_{i=1}^{n} \left[p(a_i) \left( ((1 - y_i)C(R^+, x_i)) \\
&\quad + (y_i(1 - C(R^+, x_i)))C(R^-, x_i) \\
&\quad + (1 - C(R^+, x_i))(1 - C(R^-, x_i)) \\
&\quad \times (y_i(1 - h_i) + h_i(1 - y_i)) \right] \\
\]

And \( \omega(D,R) \) represents the costs of reconciling contradicting AI recommendations incurred by the human DM:

\[
\omega(D,R) = \alpha \sum_{i=1}^{n} \left[ (1 - h_i)C(R^+, x_i)) \\
&\quad + (h_i(1 - C(R^+, x_i)))C(R^-, x_i) \right]
\]

C TeamRules Algorithm

The TeamRules (TR) algorithm is shown in Algorithm 1.

D c-HyRS Algorithm

Our modification of HyRS is shown in Algorithm 2. We use the original terminology and structure found in Wang (2019) where \( \Lambda(R, f_b, D) = \ell(R, f_b, D) + \alpha \sum_{i=1}^{N} 1[y \neq \hat{y}_b] \). \( \hat{y} \) is generated using the decision rule in Eq. 7. Note that in our setting, \( f_b \) is the human DM, and so we write \( \hat{y}_b \) as \( h \).

E Experiment Details

E.1 Checkers Dataset

- Train Instances: 4,000
Algorithm 1 TeamRules

1: Input: $D$
2: Parameters: $T, \alpha, C_0, \beta_0, \beta_1, \beta_2, q$
3: $\Gamma^+ \leftarrow$ RF-Generated Positive Candidate Rule Set
4: $\Gamma^- \leftarrow$ RF-Generated Negative Candidate Rule Set
5: $R_0 \leftarrow \text{sample}(\Gamma^+, 3) + \text{sample}(\Gamma^-, 3)$
6: $R^* \leftarrow R_0$
7: for $t = 1 \ldots T$ do
8:     $R_t \leftarrow R_{t-1}$
9:     for $i = 0 \ldots n$ do
10:         $\phi_i \leftarrow L(x_i, R_t)$ \hspace{1cm} > $L$ defined in Eq. 8
11:     if $\text{randint}(0, 1)$ then
12:         $\epsilon \leftarrow \text{argmax}(\phi)$
13:     else
14:         $Q \leftarrow \text{quantile}((\phi, q))$
15:         $\epsilon \leftarrow \text{sample}(\{i | \phi_i \geq Q\}, 1)$
16:     if $\langle R_{t-1}, x \rangle$ and $(\hat{y}_e \neq y_e)$ or $(h_e \neq \hat{y}_e)$ then
17:         if $(y_e = 0)$ then
18:             $R_t \leftarrow$ cut rule from $R_t^+$ that covers $x_e$
19:         else
20:             if $\text{randint}(0, 1)$ then
21:                 $R_t \leftarrow$ add rule to $R_t^+$ to cover $x_e$
22:             else
23:                 $R_t \leftarrow$ cut rule from $R_t^-$ that covers $x_e$
24:     else
25:         $R_t \leftarrow$ add rule to $R_{t-1}^{sign(y_e)}$
26:     if $L(D, R_t) < L(D, R_{t-1})$ then
27:         $R^* \leftarrow R_t$
28:     if $\exp\left(\frac{L(D, R_{t-1}) - L(D, R_t)}{C_0^+}\right) \leq \text{random()}$ then
29:         $R_t \leftarrow R_{t-1}$
30: Output: $R^*$

- Test Instances: 800
- Features $x^{[1]}, x^{[2]}$ are each i.i.d $\text{Uniform}(0, 2)$ r.v.
- $y = \mathbb{I}\{x^{[1]} \leq 1\} \mathbb{I}\{x^{[2]} \geq 1\} + \mathbb{I}\{x^{[1]} \geq 1\} \mathbb{I}\{x^{[2]} \leq 1\}$
- Human has 80% accuracy when $x^{[1]} > x^{[2]}$, otherwise has 100% accuracy.
- Rational Behavior: $a = 1$ (accept) in lower accuracy region, otherwise $a = 0$ (reject)
- Neutral Behavior: $a = 1$ (accept) when $x^{[1]} > x^{[2]}$, otherwise $a = 0$ (reject)
- Irrational Behavior: $a = 0$ (reject) lower accuracy region, otherwise $a = 1$ (accept)

E.2 Gaussian Dataset

- Train Instances: 4,000
- Test Instances: 800
- Features $x^{[1]} \ldots x^{[20]}$ are each i.i.d $\mathcal{N}(0, 1)$ r.v.
- Given:
  - $\varphi(x)$ is the standard normal p.d.f
  - $q_{0.5}(v)$ is the median value of vector $v$
  - $v_1 = \varphi(\sum_{d=1}^2 x^{[d]})$
Algorithm 2 c-HvRS

1: **Input:** $f_t, D, \theta_1, \theta_2, C_0$
2: **Initialize:**
3: $R^* = R[0] \leftarrow \emptyset$ \triangleright start with a pure black-box model
4: $\Upsilon^+ \leftarrow \text{FPGrowth}(D, \text{minsupp} = N \theta_1)$
5: $\Upsilon^- \leftarrow \text{FPGrowth}(D, \text{minsupp} = \frac{N \theta_1}{T}) \quad \triangleright$ mine candidate rules from $D$
6: for $t = 0 \rightarrow T$ do
7: if $\epsilon \in \{ |\{f_t(x_k) \neq y_k \} \}$ \triangleright indices of misclassified examples.
8: if $\epsilon \in \text{covrg}(R\{t\})$ then
9: if $\epsilon$ is negative then
10: $R_{t+1} \leftarrow \text{remove a rule from } R_{+\{t\}}$ that covers $\epsilon$.
11: else
12: $R_{t+1} \leftarrow \text{add a rule to } R_{+\{t\}}$ to cover $\epsilon$ or remove a rule from $R_{-\{t\}}$ that covers $\epsilon$
13: else
14: accept $R_{t+1}$ with probability $\exp\left(\frac{\Lambda(R\{t\}) - \Lambda(R\{t+1\})}{C_0}\right)$
15: $R^* = \arg \min_{R_{t+1}, R^*} \Lambda(R)$ \quad \triangleright$update the best solution$
16: Output: $R^*$

\[ v_2 = \varphi\left(\sum_{d=1}^{4} x^{[d]}\right) + \varphi\left(\sum_{d=5}^{8} x^{[d]}\right) + \varphi\left(\sum_{d=9}^{16} x^{[d]}\right) + \varphi\left(\sum_{d=17}^{20} x^{[d]}\right) \]

- $y = 1$ IFF:
  \[ \left[ \sum_{d=1}^{20} x^{[d]} < 0 \right] \text{AND } \left( v_1 > g_{0.5}(v_1) \right) \]
  OR
  \[ \left[ \sum_{d=1}^{20} x^{[d]} \geq 0 \right] \text{AND } \left( v_2 \leq g_{0.5}(v_2) \right) \]

Intuitively, if the sum of features is less than 0, the label is a simple function of $x^{[1]}$ and $x^{[2]}$. Otherwise, it is a complex function of all features.

- Human is created by first training a logistic regression model $p(y|x)$ on an excluded subset of the training data. Next, human accuracy is set to 50% wherever $2|p(y|x) - 0.5| > 0.5$, otherwise human accuracy is set to 100%.
- Rational Behavior: $a = 1$ (accept) in lower accuracy region, otherwise $a = 0$ (reject)
- Neutral Behavior: $a = 0$ (accept) when $\sum_{d=1}^{20} x^{[d]} < 0$, otherwise $a = 1$ (reject)
- Irrational Behavior: $a = 0$ (reject) lower accuracy region, otherwise $a = 1$ (accept)

E.3 FICO, Adult, HR Datasets

- Train Instances: 9,459(FICO); 23,499(Adult); 390(HR)
- Test Instances: 1,892(FICO); 4,700(Adult); 78(HR)
- Human is created by first training a logistic regression model $p(y|x)$ on an excluded subset of the training data. Next, human accuracy is set to 50% wherever:
  - $2|p(y|x) - 0.5| > 0.5$, otherwise human accuracy is set to 100%. (FICO & HR)
  - $0.5 < 2|p(y|x) - 0.5| < 0.8$. Human accuracy set to 100% when $0 < 2|p(y|x) - 0.5| < 0.4$. Remaining human decision are original logistic regression model output decision. (Adult)
- Rational Behavior: $a = 1$ (accept) in lower accuracy region, otherwise $a = 0$ (reject)
- Neutral Behavior: $a = 1$ (accept) IFF:
- \( \text{ExternalRiskEstimate} 65.0 \geq 65 \)
  AND \( \text{NumSatisfactoryTrades} 24.0 \geq 24 \). (FICO)
- \( \text{occupation}_\text{Exec-managerial} = 1 \) (Adult)
- \( \text{\'RelationshipSatisfaction} 3.0' \geq 3 \)
  AND \( \text{StockOptionLevel} = 0 \). (HR)

- Irrational Behavior: \( a = 0 \) (reject) lower accuracy region, otherwise \( a = 1 \) (accept)

### E.4 Training Parameters

- \( T = 500 \)
- \( C_0 = 0.01 \)
- \( \beta_0 = 0.05 \)
- \( \beta_1 = 1 \) for Checkers dataset, \( \beta_1 = 3 \) for all other datasets
- \( \beta_2 = 10,000 \)
- \( q = 0.05 \)

### F Complete Experiment Results

Figure 5: Results from varying contradiction cost parameter for Checkers and Gaussian datasets.
Figure 6: Results from varying contradiction cost parameter for Adult and HR datasets.

Figure 7: TR trained on Gaussian dataset with decreasing discretion model $\hat{p}(a|x)$ accuracy, averaged over 10 runs with randomized 80-20% train-test split on each run.