Towards Improving Life-Long Learning Via Personalized, Reciprocal Teaching

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***Abstract*—In a world with ubiquitous robots, robots will need to be personalizable and capable of learning novel tasks from humans throughout their deployment. However, research has shown that humans can be poor teachers [7], making it difficult for robots to effectively learn from humans. In prior work, we introduced Mutual Information Driven Meta-Learning from Demonstration (MIND MELD), which learns to map suboptimal human demonstrations to higher-quality demonstrations [10]. While this work effectively accounts for suboptimality on novel tasks within a set distribution of calibration tasks, MIND MELD does not convey to the demonstrator the way in which the demonstrator is suboptimal. If the human could learn how to provide better demonstrations, then the human might be able to effectively teach a broader range of novel, out-of-distribution tasks where MIND MELD does not readily account for potential demonstration suboptimality. In this work, we introduce Reciprocal MIND MELD, a framework in which the robot learns the way in which a demonstrator is suboptimal and utilizes this information to provide feedback to the demonstrator to improve their demonstrations long-term. In a human-subjects experiment, we demonstrate that the robot can effectively improve how a human provides feedback ($p < .001$). Additionally, we show that humans trust the robot more ($p = .014$) and feel more team fluency when the robot provides helpful advice ($p = .014$).**

***Index Terms*—meta-learning, personalization, life-long learning, imitation learning**

I. Introduction

When an individual purchases an in-home cleaning robot, the robot will have to be taught many novel tasks over an extended period of time. The user may have to teach the robot how to move dishes from their dishwasher to the proper location in the cabinets or how to wash the windows and take out the trash. To optimize the long-term relationship between the user and robot, the robot must be capable of successfully learning new tasks quickly. However, prior work has shown that humans tend to provide low-quality demonstrations to robots, making it difficult for robots to learn novel tasks [1], [3], [6], [10], [11]. Such suboptimality, if left uncorrected, is likely to hinder the robot's long-term ability to learn from end-users and degrade the human-robot relationship over time.

In prior work, Schrum et al. introduced MIND MELD [10], a personalized algorithm which meta-learns an individual-specific embedding describing a teacher's suboptimal tendencies. MIND MELD utilizes this embedding to map suboptimal labels to better labels. While prior work has shown that MIND MELD can improve a robot's ability to learn from heterogeneous, non-expert demonstrators over a short time frame [9], simply correcting suboptimality under-the-hood may not be the best long-term strategy. Doing so may 1) contribute to end-users' lack of functional understanding, 2) reinforce suboptimal tendencies, and 3) result in poor performance on out-of-distribution tasks and novel robotic platforms.

Many non-expert users lack a functional understanding of the robotic systems they are teaching, which may contribute to their suboptimal tendencies. This lack of understanding is concerning because prior work has shown that trust and reliance decrease when the end-user does not understand how the robot operates [1], [5]. Furthermore, in the MIND MELD framework, because an underlying algorithm is correcting for teacher suboptimality, the teacher will likely never learn to be a better demonstrator. Producing positive results from poor demonstrations will only reinforce the teacher's suboptimal tendencies, thereby preventing the teacher from improving. Reinforcing low quality and suboptimal demonstrator tendencies will likely have long-term consequences. For example, when the teacher provides demonstrations to a different robotic platform that may be incapable of correcting for demonstrator suboptimality, the robot will struggle to learn from the teacher. Furthermore, humans may generalize better than MIND MELD to out-of-distribution tasks and, if they are capable of providing high-quality demonstrations, will be more effective teachers in these out-of-distribution tasks.

Consequently, there is a need for a framework that can learn from suboptimal demonstrators while simultaneously coaching demonstrators to become better teachers. Our objective is to increase functional understanding, increase quality of teacher's demonstrations, and improve end-users' ability to teach novel robotic platforms and out-of-distribution tasks. To solve this problem, we employ the idea of *reciprocal teaching* from the teaching and education literature [2]. Reciprocal teaching describes a learning strategy in which the student takes on the role of the teacher. Our objective is to employ a reciprocal teaching strategy which we call Reciprocal Mutual Information Driven Meta-Learning from Demonstration

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(Reciprocal MIND MELD). In Reciprocal MIND MELD, the robot periodically assumes the role of teacher to improve end-users' demonstrations. We illustrate that Reciprocal MIND MELD can alter the way in which an individual provides demonstrations to a robot ($p < .001$) and also improves team trust ($p = .014$) and fluency ($p = .014$).

II. Preliminaries

Reciprocal MIND MELD is based on the MIND MELD architecture demonstrated in previous work [10]. In this section we provide an overview of the MIND MELD architecture.

The objective of MIND MELD is to learn a personalized embedding to describe the way in which a demonstrator is suboptimal in a robot-centric learning from demonstration paradigm. MIND MELD then utilizes this embedding to map a demonstrator's suboptimal demonstrations to demonstrations closer to the optimal. The MIND MELD architecture is trained via *calibration tasks* which are used to learn the mapping from suboptimal labels to better labels and learn the personalized embedding. The calibration tasks consist of a set of pre-recorded policy rollouts with known ground truth labels. These ground truth labels are determined via RRT* and an MPC controller and are only necessary for the calibration tasks. Participants provide corrective demonstrations to the agent during these rollouts to direct the agent to a goal. MIND MELD learns to map the participant provided corrective labels to higher-quality labels. We demonstrated MIND MELD in a driving simulator domain where the objective is to provide corrective feedback to direct the car to a goal.

The personalized embedding, $w^{(p)}$, represents the way in which an individual is suboptimal (e.g., in a driving simulator domain, an individual may over- or under-correct). To learn $w^{(p)}$, MIND MELD employs a network architecture with three subnetworks: $\mathcal{E}_{\phi'}$, f_θ, and q_ϕ. $\mathcal{E}_{\phi'}$, maps corrective feedback from the calibration tasks to encoding, $z^{(p)}_{t-\Delta t:t+\Delta t}$. f_θ maps encoding, $z^{(p)}_{t-\Delta t:t+\Delta t}$, and the personalized embedding, $w^{(p)}$, to $\hat{d}^{(p)}_t = o_t - a^{(p)}_t$ (i.e., the difference between the optimal ground truth label, o_t, and the human's corrective label, $a^{(p)}_t$). q_ϕ maps the difference, $\hat{d}^{(p)}_t$, and encoding, $z^{(p)}_{t-\Delta t:t+\Delta t}$, to a posterior distribution over the embedding, $w^{(p)}$. To ensure that $w^{(p)}$ can represent various and distinct feedback styles, we maximize a lower bound on mutual information between $d^{(p)}_t$ and $w^{(p)}$ via variational inference [4]. An overview of the MIND MELD architecture can be found in the Appendix.

III. Methodology

Because humans have a greater ability to generalize to novel tasks and domains than a machine-learning algorithm, our objective is to provide demonstrators with knowledge about how to improve their demonstrations rather than correcting suboptimality under-the-hood. To accomplish this objective, we propose an approach to shift a demonstrator's embedding towards an embedding representing a "perfect demonstrator" via robotic feedback. By doing so, we aim to improve upon an individual's ability to provide high-quality feedback to a robot and consequently improve upon the long-term relationship between demonstrator and robot. We break the problem of improving upon a demonstrator's teaching abilities into three steps. First, we learn an embedding space that is semantically meaningful so as to determine and communicate to the demonstrator the way in which they are suboptimal. Next, based upon where an individual falls within this embedding space, we provide robotic feedback to the demonstrator that is descriptive and actionable. Third, we re-estimate the individual's embedding to determine if the embedding is sufficiently close to the perfect embedding.

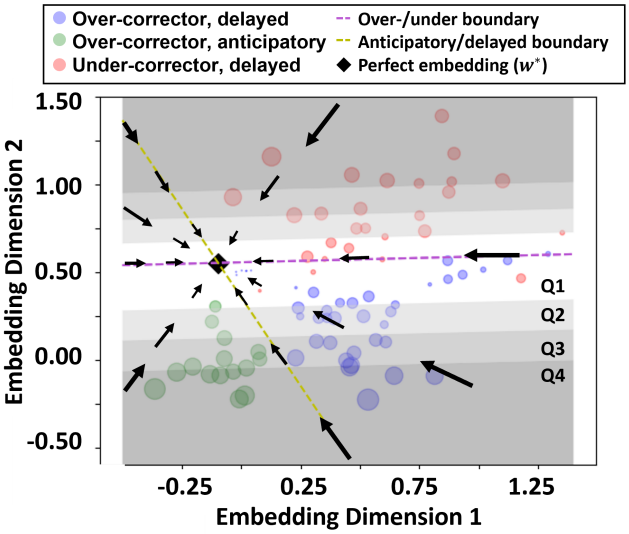

Fig. 1: This figure shows the learned embedding space and decision boundaries. Each point represents the embedding of a demonstrator, and the diameter represents the magnitude of over-/under correction. The arrows indicate the direction an embedding should move to be closer to the perfect embedding. Blue points represent participants who tend to over-correct and are delayed, red under-correct and are delayed, and green over-correct and are anticipatory. Q1-Q4 indicate quartiles one through four for the over-/under-correcting dimension.

A. Semantically Meaningful Embedding Space

We illustrated in prior work [10] that MIND MELD learns personalized embeddings that correlate with suboptimal stylistic tendencies. In the driving simulator domain, we show that the embeddings correlate with a participant's tendency to over-/under-correct and provide delayed/anticipatory demonstrations. We utilize the location of the demonstrator's embedding within the embedding space to translate a demonstrator's personalized embedding into actionable robotic feedback.

To aid in learning a semantically meaningful embedding space, we add an additional loss when learning the embedding space. We utilize a mean squared error (MSE) loss to train the network to predict the suboptimal tendency (i.e., the magnitude by which a demonstrator over-/under corrects and is delayed/anticipatory) given the personalized embedding. This loss helps to ensure that our embedding space can be translated into actionable robotic feedback. We learn the embedding

space by training on data from 72 calibration participants collected in previous work [9]. The ground truth suboptimal magnitude is determined via dynamic time warping (DTW) [8] between the participants' feedback and the ground truth labels. Because MIND MELD outputs the difference between the participant's corrective labels and the ground truth, the perfect demonstrator's embedding, w^*, is defined as the embedding which minimizes the output of the MIND MELD architecture as described in Eq. 1.

$$w^* = \underset{w^{(p)}}{\operatorname{argmin}} \sum_{t,p} f_\theta\Big(\mathcal{E}_{\phi'}(a^{(p)}_{(t-\Delta t:t+\Delta t)}), w^{(p)}\Big) \quad (1)$$

Our next objective is to determine the semantically meaningful dimensions of the embedding space. We train a support vector machine (SVM) with a linear kernel to learn the decision boundary which best separates the training participants into their respective suboptimal categories (over- vs. under-correctors and delayed vs. anticipatory). We add the additional constraint that the linear classifier must pass through the point representing the perfect demonstrator, w^*. Therefore, the distance between the embedding and the decision boundary determines the magnitude by which the demonstrator over- or under-corrects. Participants whose embeddings are farther away from a decision boundary are more suboptimal in the respective dimension.

Fig. 1 depicts our embedding space with the linear classifiers separating over-correctors from under-correctors and delayed from anticipatory. The size of the point represents the magnitude by which the demonstrator is suboptimal as determined by DTW. The plot illustrates that demonstrators which are more suboptimal (as represented by larger points) are farther away from the decision boundary, supporting our hypothesis that distance from the decision boundary can be used to measure the degree of suboptimality. To further support our claim, we apply Spearman's correlation and find that distance from the decision boundary strongly correlates with the magnitude of suboptimality ($\rho = 0.84$, $p < .001$).

B. Robotic Feedback

To determine the feedback the robot should provide, we calculate the distance along the semantically meaningful dimension between the personalized embedding, $w^{(p)}$, and the perfect demonstrator's embedding, w^*. For example, in this work we are interested in $\epsilon^{(i)}_{o/u}$, which defines the distance between the demonstrator's embedding and the hypothetical perfect demonstrator's embedding in the over-/under-correcting dimension after the i^{th} round of feedback. The robot then provides feedback that is proportional to the distance from w^*. In this exploratory work, we focus on improving upon demonstrator's tendency to over-/under-correct and, therefore, the robot only provides feedback related to this dimension.

To convert $\epsilon^{(i)}_{o/u}$ into actionable robotic feedback, we discretize the range of $\epsilon^{(i)}_{o/u}$ by splitting the embeddings from the previously collected calibration participants into quartiles. Our objective is to move a participant's embedding so that they are in the range denoting the 25% of previously collected calibration participants who under- or over-corrector the least (i.e., quartile one). Participants who fall in a quartile farther from the decision boundary receive feedback proportional to their quartile. Table I shows the feedback that is provided to the participant based upon the quartile that they fall within and whether or not the participant interacts with a cooperative or adversarial robot. The difference between a cooperative and adversarial robot and the basis for these conditions is discussed further in Section IV-B.

TABLE I: This table shows the feedback a participant receives based on their quartile and study condition.

Cooperative Quartile	Adversarial Quartile	Feedback
First	Fourth	"Your feedback is good! Keep it up."
Second	Third	"You are slightly over-/under correcting. Please turn the wheel a bit more/less."
Third	Second	"You are over-/under correcting. Please turn the wheel more/less."
Fourth	First	"You are over-/under correcting a lot. Please turn the wheel a lot more/less."

C. Re-estimating Embedding

To determine when $w^{(p)}$ has moved sufficiently close to w^* (indicating that a person's feedback has sufficiently improved), we must update $w^{(p)}$ after each iteration of robotic feedback. To re-estimate their embedding after robot feedback, the participant completes another round of the calibration tasks. In future work, we plan to re-estimate the embedding on-the-fly without the need to redo the calibration tasks by training an LSTM to predict the new embedding.

IV. Human-Subjects Study

Below we describe our study design and the three study conditions. Our objective is to demonstrate that robotic feedback can be utilized to move a participant's embedding in any direction and to show that a participant's embedding is not moving simply due to repetition of the calibration tasks.

A. Study Design

After completing demographic information and pre-study surveys, participants complete four rounds of the calibration tasks. Between each round, participants complete trust and fluency surveys and, depending on the condition they are in, the participant may receive feedback from the robot about their demonstrations. At the end of the study, participants complete workload, likeability, and intelligence questionnaires.

B. Conditions

Cooperative Teacher: In the Cooperative condition, the robot provides feedback to improve the demonstrator's teaching as shown in Table I.

Adversarial Teacher: In the Adversarial condition, the robot provides feedback to make the participant a worse demonstrator. Adversarial therefore provides feedback that is opposite of Cooperative (Table I). The purpose of this condition is to determine whether feedback generally or quality of feedback positively influences a participant's teaching abilities.

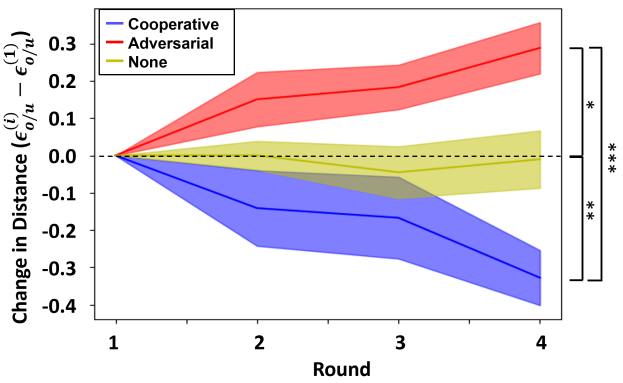

Fig. 2: This figure shows the difference between the embedding distance ($\epsilon^{(i)}_{o/u}$) at round, i, and the embedding distance at round one ($\epsilon^{(1)}_{o/u}$) for the three conditions.

No Teacher (None): In the None condition, the participant does not receive any feedback from the robot.

V. Results

We recruited 27 participants (Mean age = 24.15, SD = 3.4; 37.0% Female) to participate in our study. In this section, we report results related to both the objective ability of the agent to alter the participant's embedding and the subjective perception of the agent. We verify all data meets parametric assumptions before applying a parametric test.

a) Objective Results: Fig. 2 shows the change in the distance ($\epsilon^{(i)}_{o/u} - \epsilon^{(1)}_{o/u}$) in the over-/under correcting dimension between round one and rounds one through four. We plot $\epsilon^{(i)}_{o/u} - \epsilon^{(1)}_{o/u}$ to show how participants change irrespective of their initial teaching skill. The plot illustrates that robotic feedback is able to shift a participant's embedding closer to w^* in the Cooperative condition and farther from w^* in the Adversarial condition. In the Appendix, we illustrate that the amount by which a participant over-/under-corrects as calculated by dynamic time-warping is similarly affected by robotic feedback, further supporting our hypothesis that $\epsilon_{o/u}$ correlates with the tendency to over-/under-correct.

We conduct a repeated-measures ANOVA to determine if the distance at round one, $\epsilon^{(1)}_{o/u}$, significantly differs from the distance, $\epsilon^{(4)}_{o/u}$, at round four. We find that $\epsilon^{(1)}_{o/u}$ is significantly larger ($M = 0.47$, $SD = 0.20$) compared to $\epsilon^{(4)}_{o/u}$ ($M = 0.14$, $SD = 0.07$) in Cooperative ($F(1,8) = 22.56$), $p = .001$). We additionally find significance ($F(1,8) = 20.06$, $p = .002$) between $\epsilon^{(1)}_{o/u}$ ($M = 0.37$, $SD = 0.20$) and $\epsilon^{(4)}_{o/u}$ ($M = 0.67$, $SD = 0.11$) in Adversarial. We find no significant difference with None ($\epsilon^{(1)}_{o/u}$: $M = 0.31$, $SD = 0.25$; $\epsilon^{(4)}_{o/u}$: $M = 0.30$, $SD = 0.22$; $F(1,8) = 0.02$, $p = .89$).

We next apply a one-way ANOVA with Tukey post-hoc to compare $\Delta\epsilon_{o/u}$ across conditions, where $\Delta\epsilon_{o/u} = \epsilon^{(1)}_{o/u} - \epsilon^{(4)}_{o/u}$. $\epsilon^{(1)}_{o/u}$ is the distance from the perfect embedding in round one and $\epsilon^{(4)}_{o/u}$ is the distance in round four. We find that the Adversarial condition results in the embedding shifting significantly farther from the perfect embedding between rounds one to four ($F(2,24) = 20.21$, $p < .001$) compared to Cooperative ($p < .001$) and None ($p = .014$). We additionally find that Cooperative results in the embedding shifting significantly closer to the perfect embedding ($p = .009$) compared to None. These findings suggest that robotic feedback is capable of shifting a participant's embedding both farther from and closer to w^*. The fact that None does not significantly alter $w^{(p)}$ suggests that participants are not simply improving due to repeated interactions and supports the hypothesis that the embeddings are instead shifting due to the robotic feedback. Additionally, the fact that participants in the adversarial condition move significantly farther from w^* suggests that Reciprocal MIND MELD is able to directly modulate human behavior.

b) Subjective Results: Table II shows the results of the subjective metrics. By applying a one-way ANOVA with Tukey post-hoc, we find that participants' trust increased significantly more ($F(2,24) = 5.2$, $p = .014$) in Cooperative compared to Adversarial ($p = .020$) and None ($p = .038$). We do not find significance between Adversarial and None. Similar trends emerge for change in team fluency. We find that participants report statistically significantly greater positive change in fluency ($F(2,24) = 5.1$, $p = .014$) in Cooperative compared to Adversarial ($p = .017$) and close to significant change compared to None ($p = .052$). Again, we do not find significant difference between Adversarial and None.

While we do not find significance between conditions with regards to the other subjective metrics, we do note some trends that merit discussion. Surprisingly, we find that Cooperative is rated as requiring lower workload compared to Adversarial and None, despite participants likely having to exert additional mental effort to comply with the demands of the robot. We also find that the Cooperative robot is rated as more intelligent compared to both the Adversarial and None teachers.

TABLE II: This table shows the mean and standard deviation of the subjective metrics and $\Delta\epsilon_{o/u}$. Δ Trust and Δ Fluency describe the change in Trust and Fluency respectively between rounds one and four.

	Cooperative	**Adversarial**	**None**	p-value
$\boldsymbol{\Delta\epsilon_{o/u}}$	0.33 (0.2)	-.30 (0.2)	0.01 (0.2)	$\boldsymbol{p < .001}$
Workload	37.5 (16.4)	46.1 (19.5)	53.5 (11.6)	$p = .13$
Likeability	6.69 (2.0)	6.81 (1.5)	6.86 (1.4)	$p = .98$
Intelligence	6.31 (1.6)	5.57 (1.1)	6.24 (1.4)	$p = .37$
Δ Trust	0.56 (.4)	-0.01 (0.4)	.05 (0.2)	$\boldsymbol{p = .014}$
Δ Fluency	0.34 (0.4)	-0.13 (0.3)	-0.04 (0.4)	$\boldsymbol{p = .014}$

VI. Conclusion and Future Work

In future work we plan to conduct a study investigating if we can simultaneously improve a demonstrator's tendencies to both over-/under correct and provide delayed/anticipatory feedback. We next will conduct a study to determine if the robotic feedback and improved teaching abilities translate to better learning outcomes for the robot. Lastly, we will investigate how Reciprocal MIND MELD impacts teaching abilities in a longitudinal study in which participants return for repeat interactions and teach a robot over a period of weeks.

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Appendix

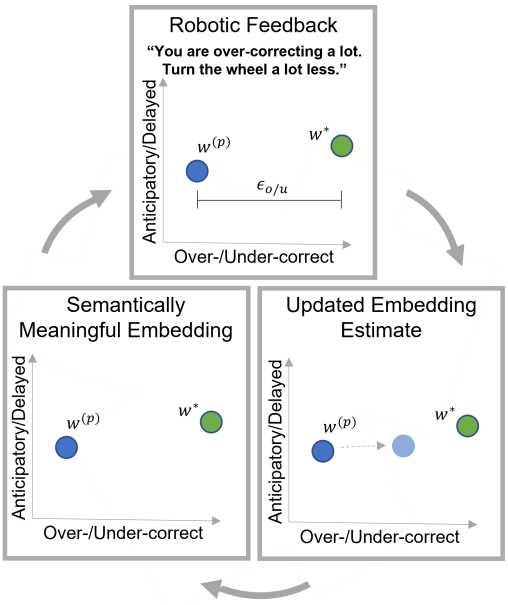

Fig. 1: This figure shows our Reciprocal MIND MELD framework. $\epsilon_{o/u}$ is the distance from the perfect embedding, w^*, along the over-/under-correcting dimension.

I. Reciprocal MIND MELD Architecture

Fig. 1 shows the steps in the Reciprocal MIND MELD framework. To determine the robotic feedback that should be provided to the demonstrator, we first learn a semantically meaningful embedding space. The robot then provides feedback to the demonstrator based upon the distance from the perfect embedding in each semantically meaningful dimension. For example, the robot provides feedback in the over-/under-correcting dimension based on the distance, $\epsilon_{o/u}$. We then re-estimate the embedding after robotic feedback. In our study, participants experience four rounds of robotic feedback. Between rounds, if the participants improves their feedback but is still not within the first quartile, the robot says, "That is better but..." followed by the appropriate feedback.

II. Additional Results

Fig. 2 shows the change in the distance $(\epsilon^{(4)}_{o/u} - \epsilon^{(1)}_{o/u})$ in the over-/under correcting dimension between round one and rounds one through four. Fig. 3 shows the change between rounds one and four in the amount by which the participant under-/over corrects as calculated via dynamic time warping (DTW) between the participant demonstrations and the ground truth labels. The similarity in trends between Fig. 2 and 3 suggests that robotic feedback is not only able to shift a participant's embedding but it is also able to alter the amount by which a participant over-/under-corrects. This finding lends

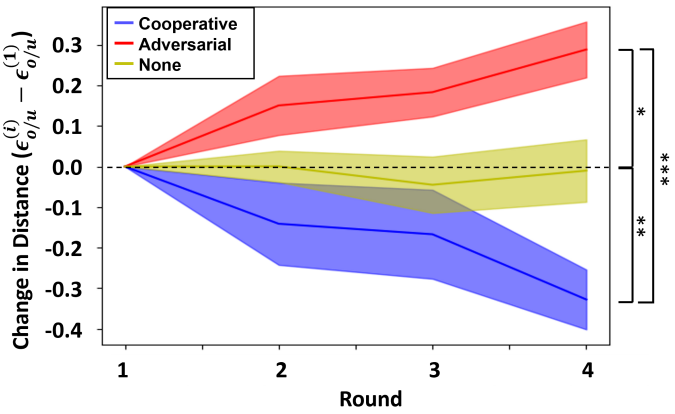

Fig. 2: This figure shows the difference between the embedding distance at each round, $\epsilon_{o/u}$, and the embedding distance at round one, $\epsilon^{(1)}_{o/u}$, for the three conditions.

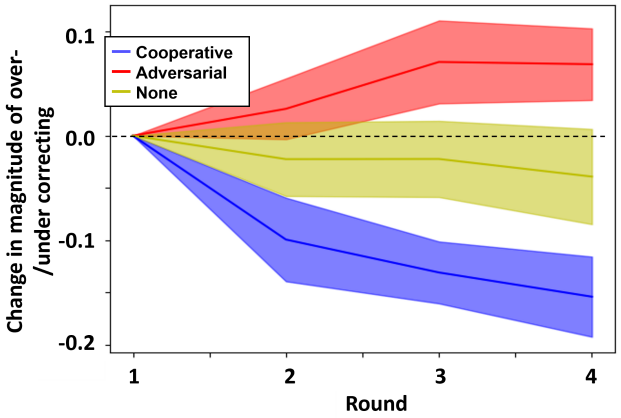

Fig. 3: This figure shows the average amount and standard error by which participants over- and under-correct at each round minus the amount by which a participant over-/under corrects in round one as calculated by dynamic time warping with the ground truth labels.

support to the idea that the distance from the embedding to the decision boundary is a good measure of how much a participant over-/under-corrects.

Because data does not meet parametric assumptions, we apply Friedman's test to determine if there is a statistically significant difference in how much an individual over-/under-corrects in round one versus round four as determined via DTW. We find that participants over-/under-correct significantly less in round four compared to round one in the Cooperative condition ($\chi^2(1) = 9$, $p = .0027$). We find that the opposite is true in the Adversarial condition, with

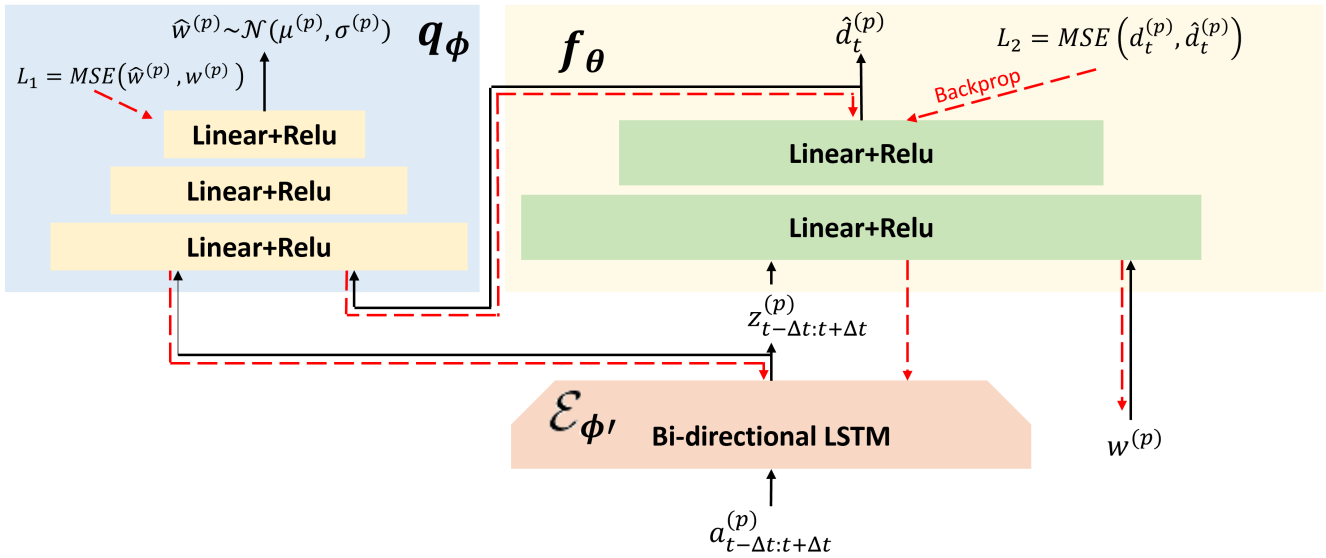

Fig. 4: This figure shows the MIND MELD network architecture. The inputs to the architecture are a demonstrator, p's, corrective labels, $a^{(p)}_{(t-\Delta t:t+\Delta t)}$, from time $t-\Delta t$ to $t+\Delta t$ and the personalized embedding, $w^{(p)}$. The bi-directional LSTM extracts sequential information about the demonstrator's feedback. The f_θ subnetwork learns the predicted difference, $\hat{d}_t^{(p)}$, by minimizing the mean squared error (MSE) between $\hat{d}_t^{(p)}$ and the true difference, $d_t^{(p)} = a_t^{(p)} - o_t$, between the demonstrator's corrective feedback, $a_t^{(p)}$, and the ground truth label, o_t. The re-creation subnetwork q_ϕ maximizes mutual information between the personalized embedding, $w^{(p)}$, the encoding $z^{(p)}_{(t-\Delta t:t+\Delta t)}$, and the learned difference, $\hat{d}_t^{(p)}$ to estimate the learned embedding, $\hat{w}^{(p)}$ [3], [4].

participants over-/under-correcting more in round four versus round one ($\chi^2(1) = 5.44$, $p = .0196$). We do not find a significant difference for the None condition ($\chi^2(1) = .111$, $p = .74$).

III. MIND MELD Architecture

A. Network Architecture

Fig. 4 shows the MIND MELD architecture. The three main components of the architecture are: 1) the bi-directional long short-term memory (LSTM) encoder, $\mathcal{E}_{\phi'}: A \rightarrow Z$, 2) the prediction subnetwork, $f_\theta: Z \times W \rightarrow \mathbb{R}$, and 3) the mutual information subnetwork, $q_\phi: Z \times \mathbb{R} \rightarrow \mathcal{N}_W$. Our goal is to improve upon the corrective feedback, $a_t^{(p)}$, from a demonstrator, p. The corrective feedback from the human demonstrator from $t-\Delta t : t+\Delta t$ is fed into the bi-directional LSTM, $\mathcal{E}_{\phi'}$, to extract an encoding, $z^{(p)}_{t-\Delta t:t+\Delta t}$. The f_θ subnetwork takes in the encoding, $z^{(p)}_{t-\Delta t:t+\Delta t}$, and the personalized embedding, $w^{(p)}$, and learns the predicted difference, $\hat{d}_t^{(p)}$, between the optimal ground truth label, o_t, and the human's corrective label, $a_t^{(p)}$. The q_ϕ subnetwork learns to map the difference, $\hat{d}_t^{(p)}$, and the encoding, $z^{(p)}_{t-\Delta t:t+\Delta t}$, to a posterior distribution over the person's embedding, $w^{(p)}$. We estimate an individual's learned embedding, $\hat{w}^{(p)}$, by sampling from the approximate posterior [2]. $w^{(p)}$ is initialized based upon the prior, $\hat{w}^{(p)} \sim \mathcal{N}(0, 1)$.

B. Variational Inference

We assume that humans provide heterogeneous and distinct styles when providing corrective feedback to the robot. A person's corrective style is encapsulated in the embedding, $w^{(p)}$, for person, p. To learn $w^{(p)}$, we maximize the lower bound on the mutual information between the learned embedding, $w^{(p)}$, and the predicted difference between the human feedback and the optimal feedback, $\hat{d}_t^{(p)}$ (Eq. 1). Intuitively, maximizing mutual information means that observing the difference, $\hat{d}_t^{(p)}$ will reduce uncertainty about the personalized embedding.

In Eq. 1, the mutual information between $z^{(p)}$, $\hat{d}_{t'}^{(p)}$, and personalized embedding, $w^{(p)}$, is denoted as $I(w^{(p)}; z^{(p)}, \hat{d}_{t'}^{(p)})$. However, maximizing the mutual information requires access to an intractable posterior distribution, $P(w^{(p)}|z^{(p)}, \hat{d}_t^{(p)})$, therefore, we employ variational inference and the evidence lower bound to estimate the distribution using q_ϕ [1]. The variational lower bound is $L_I(f_{\theta|w}, q_{\phi|\theta})$.

$$I(w^{(p)}; z^{(p)}, \hat{d}_t^{(p)}) = H(w^{(p)}) - H(w^{(p)}|z^{(p)}, \hat{d}_t^{(p)}) \geq \quad (1)$$
$$\mathbb{E}[log(q_\phi(w^{(p)}|z, \hat{d}_t^{(p)}))] + H(w^{(p)}) = L_I(f_{\theta|w}, q_{\phi|\theta})$$

The MIND MELD architecture utilizes two loss functions, one to learn the personalized embedding, $w^{(p)}$, and another to learn the amount that a person's feedback is suboptimal, $\hat{d}_{t'}^{(p)}$, as shown in Fig. 4. For the q_ϕ subnetwork, we minimize the mean squared error between the sampled approximation of the embedding, $\hat{w}^{(p)}$, and the personalized embedding,

$w^{(p)}$, which is equivalent to maximizing the log-likelihood of the posterior. The loss function for the f_θ subnetwork is the mean squared error between the predicted difference, $\hat{d}_t^{(p)}$, and the difference between the human feedback and the optimal ground truth, $d_t^{(p)} = a_t^{(p)} - o_t$. These two losses are summed (Eq. 2) and backpropagated through the layers and the input embedding, $w^{(p)}$, so that the embedding converges to reflect a person's feedback style. At test time, the MIND MELD network parameters θ, ϕ, and ϕ' are frozen. We then backpropagate only through $w^{(p)}$, to learn an embedding that encapsulates a participant's suboptimal style.

$$L_{(\theta,\phi,\phi',w)} = L_{1_{(\theta,\phi,\phi')}} + \lambda L_{2_{(\theta,\phi')}} \tag{2}$$

$$L_{1_{(\theta,\phi,\phi')}} = \frac{1}{K+1} \sum_{k=0}^{K} ||\hat{w}_k^{(p)} - w_k^{(p)}|| \tag{3}$$

$$L_{2_{(\theta,\phi')}} = ||d_k^{(p)} - \hat{d}_k^{(p)}|| \tag{4}$$

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MIND MELD: Personalized Meta-Learning for Robot-Centric Imitation Learning

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***Abstract*—Learning from demonstration (LfD) techniques seek to enable users without computer programming experience to teach robots novel tasks. There are generally two types of LfD: human- and robot-centric. While human-centric learning is intuitive, human centric learning suffers from performance degradation due to covariate shift. Robot-centric approaches, such as Dataset Aggregation (DAgger), address covariate shift but can struggle to learn from suboptimal human teachers. To create a more human-aware version of robot-centric LfD, we present Mutual Information-driven Meta-learning from Demonstration (MIND MELD). MIND MELD meta-learns a mapping from suboptimal and heterogeneous human feedback to optimal labels, thereby improving the learning signal for robot-centric LfD. The key to our approach is learning an informative personalized embedding using mutual information maximization via variational inference. The embedding then informs a mapping from human provided labels to optimal labels. We evaluate our framework in a human-subjects experiment, demonstrating that our approach improves corrective labels provided by human demonstrators. Our framework outperforms baselines in terms of ability to reach the goal ($p < .001$), average distance from the goal ($p = .006$), and various subjective ratings ($p = .008$).**

***Index Terms*—Learning from demonstration, personalization, meta-learning**

I. Introduction

Learning from Demonstration (LfD) seeks to enable humans to teach robots new skills via human task demonstrations without the need for users to have prior experience in computer programming [2]. In LfD, the robot learns a policy that maps the state of the world to how the robot should act to accomplish the human-specified or demonstrated task [36]. Researchers have pursued two principle types of LfD: human-centric and robot-centric [22]. In human-centric LfD, a human typically performs the task, and the robot infers from this demonstration the task specification. An example of human-centric LfD is Behavioral Cloning (BC), i.e. *mimicry* [11], where the robot records the human demonstration of the task and uses supervised learning to learn a policy mapping states to actions. However, BC suffers from covariate shift issues due to a mismatch between the distribution of states given by the demonstration versus those experienced by the robot when attempting to accomplish the task [26], [31], [32].

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Robot-centric LfD is an alternative to human-centric LfD and addresses the problem of covariate shift [32] by instead learning from a human's corrective feedback signal at each time step as the robot executes the task [22]. One example of robot-centric LfD is Dataset Aggregation (DAgger) [32]. Ross et al. showed that learning from human corrective actions solves the problem posed by covariate shift [32]. Many robot-centric, as well as human-centric, LfD algorithms assume the demonstrator is an expert at the task and that they will provide optimal demonstrations or feedback [29]. When the demonstrator is a Wizard-of-Oz oracle [30] and provides optimal demonstrations, prior work has shown that DAgger can learn policies that are more sample efficient and accurate than human-centric LfD algorithms [32]. However, these studies may not translate to real-world settings where non-oracle, heterogeneous human demonstrators provide suboptimal demonstrations [1], [4], [22], [42]. Prior work has shown that humans struggle to provide high quality corrective actions during robot-centric LfD [39]. Additionally, humans are heterogeneous: the way humans provide feedback may differ depending upon the individual's abilities and prior experience [28], [35]. Therefore, robot-centric LfD approaches need to account for the teacher's suboptimality and heterogeneity to learn effective policies. However, prior work fails to take into account demonstrator suboptimality and human heterogeneity in robot-centric LfD.

To fill this gap, we aim to harness the potential advantages of robot-centric algorithms (i.e., increased policy performance and sample efficiency) and improve upon robot-centric algorithms by explicitly learning to account for heterogeneity and suboptimality in teaching. We introduce Mutual Information-driven Meta-learning from Demonstration (MIND MELD), which uses a Long Short-Term Memory (LSTM) neural network-based architecture to meta-learn a person-specific mapping from human-provided, corrective-action labels to idealized labels, which are inferred based upon a distribution of calibration tasks with known, optimal labels. Because human feedback is heterogeneous, we propose to use variational inference to learn a personalized embedding that encapsulates information about a person's style of providing corrective feedback. We then use the personalized embedding to map each individual's suboptimal labels to labels that more closely approximate optimal labels, thereby improving the performance of robot-centric LfD algorithms. Optimal labels

(i.e., ground truths) are only necessary for a small set of calibration tasks [14], [17] to learn to improve upon human labels and are not needed at test time.

In this paper, we conduct an IRB-approved within-subjects study, comparing the performance of MIND MELD to a robot-centric baseline, DAgger, and a human-centric baseline, BC. We evaluate these algorithms based on their ability to learn the task of driving an autonomous vehicle to a goal without collisions as well as various subjective metrics. Additionally, we analyze how the learned personalized embeddings capture the demonstrator's style and improve suboptimal labels.

In our work, we contribute the following:

1) We formulate MIND MELD, a novel, personalized LfD framework for improving upon suboptimal corrective labels by inferring individual demonstrator styles.
2) We demonstrate that MIND MELD objectively outperforms prior work in a human-subjects experiment in its ability to reach the goal more often than BC ($p < .001$) and DAgger ($p < .001$).
3) We show that users prefer MIND MELD over DAgger and BC in terms of trust ($p < .001$), workload ($p = .005$), perceived intelligence ($p = .008$), and likeability ($p = .004$).

II. Related Works

Prior work has explored human-centric LfD for learning a robot policy for task execution from an expert human demonstrator [2], [12], [24], [29], [32]. The simplest and most ubiquitous form of human-centric learning is BC, in which a robot infers the mapping from states to actions via supervised learning based on human demonstrations [18], [31]. However, if the learner deviates from the demonstrated path, covariate shift occurs due to a mismatch between the states induced by the demonstrations and those experienced by the robot when rolling out a policy. Due to this covariate shift, a learner's mistake count can compound quadratically with regards to the time horizon [32].

In response to this problem, Ross et al. introduced Dataset Aggregation (DAgger), a robot-centric LfD approach that aggregates a training data set of expert labels queried during policy rollout [32]. DAgger utilizes the state distribution induced by the current policy to solicit labels from the expert and employs a gating function to determine the mixture of expert and learner during each rollout. Ross et al. proved linear-loss, no-regret guarantees and showed that with high-quality, expert demonstrations, DAgger outperforms prior work.

However, Laskey et al. [22] showed that robot-centric learning approaches, such as DAgger, can lead to human mislabelling, resulting in poor learner performance. Additionally, DAgger requires a heavy workload from the demonstrator, which can result in demonstrator fatigue and poor training results [21], [23], [27]. Prior work has attempted to reduce the amount of corrective feedback required of the demonstrator by DAgger to improve teacher-learner interaction [16], [21], [25], [42]. He et al. proposed an imitation-learning-by-coaching algorithm in which the learner must imitate actions of progressively increasing difficulty [16]. In this approach, task loss is reduced by demonstrating to the learner preferable actions. Results have shown that this coaching scheme can outperform DAgger and achieve a lower regret bound when the demonstrator is an oracle, but no study has been conducted demonstrating this method's advantage with human teachers.

In related work, Kelly et al. proposed to reduce expert workload while improving upon expert-provided demonstrations through Human Gated DAgger (HG-DAgger), allowing the expert to decide when to provide feedback via a gating function [21]. HG-DAgger learns a stationary policy such that labels are obtained via a policy that stabilizes around expert trajectories. Spencer et al. expanded on this idea, utilizing both information about when the expert does and does not intervene, in the Expert Intervention Learning (EIL) algorithm [42]. HG-DAgger and EIL both focus on augmenting *when* the human should provide feedback during a trajectory, whereas our approach focuses on *how*, by improving the feedback itself. Because our approach is complimentary and orthogonal to robot-centric LfD approaches such as HG-DAgger and EIL, these approaches are not suitable benchmarks. Instead, our approach could be used in conjunction with these and other related approaches to improve upon human-provided labels.

Knox and Stone developed TAMER, which allows humans to provide feedback in the form of a scalar reward [5]. TAMER accounts for delayed feedback, but does not account for heterogeneous demonstrators. Other approaches, such as T-Rex and D-Rex, use inverse reinforcement learning (IRL) to improve upon poor human demonstrations by learning a reward function from a set of ranked demonstrations [6], [7]. Also using IRL, Chen et al. introduced SSRR to learn from suboptimal demonstrations by characterizing the relationship between noise and performance [9]. However, there is a lack of prior work accounting for both the heterogeneity and suboptimality of humans for robot-centric LfD. Therefore, there is a need for LfD algorithms that can effectively learn from the typical, non-expert human demonstrator in a robot-centric paradigm [29]. Our approach is the first to improve upon robot-centric learning by inferring demonstrator style via personalized embeddings to correct for suboptimal demonstrations. We maintain the advantages of robot-centric learning (i.e., reducing covariate shift) while making robot-centric LfD more human-aware by accounting for the suboptimality and heterogeneity of human demonstrators.

III. Methodology

In the following section, we provide an overview of the preliminaries of our work and describe our MIND MELD algorithm for improving robot-centric LfD with suboptimal human demonstrators. We discuss our network architecture, personalized embeddings, and the mapping of suboptimal labels to more effective labels.

A. Preliminaries

The LfD problem can readily be framed as a Markov Decision Process sans reward function (MDP\R). The MDP\R

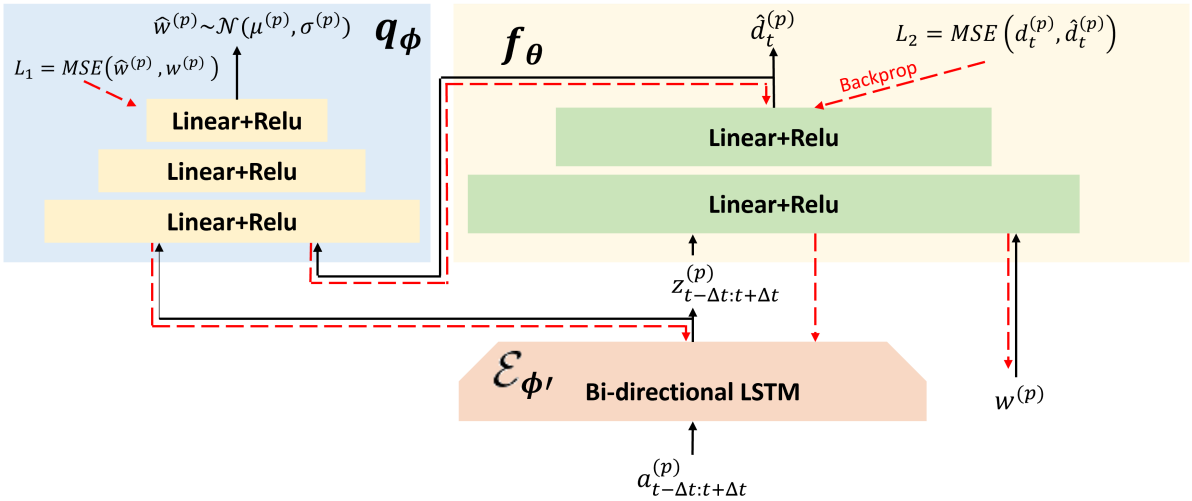


Fig. 1: This figure shows the MIND MELD network architecture. $a_t^{(p)}$ represents demonstrator p's corrective label, at time t. The recreation subnetwork, q_ϕ, maximizes mutual information between the learned embedding, $w^{(p)}$, the encoding, $z^{(p)}_{(t-\Delta t:t+\Delta t)}$, and the output, $\hat{d}_t^{(p)}$. The objective is to minimize the mean squared error (MSE) between the predicted difference, $\hat{d}_t^{(p)}$, and the true difference, $d_t^{(p)} = a_t^{(p)} - o_t$, of the demonstrator's corrective feedback and the ground truth label, o_t. We pass in the sequence of corrective feedback, $a^{(p)}_{(t-\Delta t:t+\Delta t)}$, from time $t - \Delta t$ to $t + \Delta t$ to the bi-directional LSTM and extract sequential information to inform the predictions of ground truth label at time t.

is defined by the 4-tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \gamma \rangle$. $\mathcal{S}$ represents the set of states and $\mathcal{A}$ the set of actions. $T : \mathcal{S} \times \mathcal{A} \times \mathcal{S}' \rightarrow [0, 1]$ is the transition function that returns the probability of transitioning to state, s', from state, s, applying action, a. γ weights the discounting of future rewards. Reinforcement learning seeks to synthesize a policy, $\pi : \mathcal{S} \rightarrow \mathcal{A}$, mapping states to actions to maximize the future expected reward. In an LfD paradigm, a demonstrator provides a set of trajectories, $\{(s_t, a_t), \forall t \in \{1, 2, ...T\}\}$, from which the agent learns a policy.

We make the following assumptions in our work.

- In the context of robot-centric learning from demonstration, humans provide corrective feedback that is suboptimal (e.g., with respect to an optimal, minimum-jerk, collision-free trajectory planner).
- These human-specified, heterogeneous, sub-optimal strategies can be represented by a learned embedding.
- Across different tasks, humans provide predictable and consistent, albeit suboptimal, corrective feedback.
- We have access to a distribution of calibration tasks from which we can obtain the optimal, ground truth labels.

Given these assumptions, we learn an individual's corrective "style" via a personalized embedding trained over a set of calibration tasks to represent the human's suboptimal tendencies. We then utilize this embedding to condition a meta-learned mapping from suboptimal corrective labels to ground truth labels given a set of calibration tasks. Our approach is a type of meta-learning as we learn an architecture over a distribution of tasks and participants in order to more effectively learn a specific LfD task.

B. Architecture

Depicted in Fig. 1 is the architecture of our network, which consists of three components: 1) the bidirectional LSTM encoder, $\mathcal{E}_{\phi'} : A \rightarrow Z$, 2) the prediction subnetwork, $f_\theta : Z \times W \rightarrow \mathbb{R}$, and 3) the mutual information subnetwork, $q_\phi : Z \times \mathbb{R} \rightarrow \mathcal{N}_W$. The label we aim to improve upon is $a_t^{(p)}$. We denote the set of d-dimensional, personalized embeddings as W, and the set of k-dimensional encodings extracted from the sequences of corrective feedback as $Z \subset \mathbb{R}^k$. $\mathcal{E}_{\phi'}$ is trained to extract the encoding, $z^{(p)}_{(t-\Delta t:t+\Delta t)} \in Z$, for the sequence of corrective labels, $a^{(p)}_{(t-\Delta t:t+\Delta t)}$, provided by person p from time $t - \Delta t$ to $t + \Delta t$.

f_θ maps the encoding, $z^{(p)}_{(t-\Delta t:t+\Delta t)}$, and personalized embedding, $w^{(p)}$, to the difference, $d_t^{(p)} = o_t - a_t^{(p)}$, between the ground truth label (obtained via a controller such as MPC [8] or Stanley [41]) and the individual's corrective label, where $d_t^{(p)} \in \mathbb{R}^k$. The subnetwork q_ϕ learns a mapping of the encoding, $z^{(p)}_{(t-\Delta t:t+\Delta t)}$, and predicted difference, $\hat{d}_t^{(p)}$, to a posterior distribution over the demonstrator's embedding, $w^{(p)}$. We initialize $w^{(p)}$ based upon the prior, $\hat{w}^{(p)} \sim \mathcal{N}(0, 1)$, and obtain an estimate of the individual's learned embedding, $\hat{w}^{(p)}$, by sampling from the approximate posterior.

C. Variational Inference

This work is motivated by the assumption that humans are not optimal or homogeneous in how they provide feedback, thus necessitating democratized LfD methods which account for both heterogeneity and suboptimality. Note that we handle the fact that individuals' demonstrations are suboptimal and heterogeneous separately. We capture information about an

individual's corrective "style" (i.e., *how* they are suboptimal) using a personalized embedding, $w^{(p)}$, for individual p, which we then use to correct the individual's suboptimal and heterogeneous demonstrations, as described in Eq. 1. In our work, we seek to maximize the mutual information between the corrective mapping, $\hat{d}_t^{(p)}$, our learned personalized embedding, $w^{(p)}$, and the encoding of the demonstrator labels, $z^{(p)}_{(t-\Delta t:t+\Delta t)}$, such that the uncertainty of our learned embedding decreases, given informative corrective feedback.

Maximizing mutual information necessitates access to an intractable posterior distribution, $P[w^{(p)}|z^{(p)}_{(t-\Delta t:t+\Delta t)}, \hat{d}_t^{(p)}]$. Thus, we train $w^{(p)}$ to capture salient information about an individual's style by utilizing the variational lower bound, $L_I(f_\theta, q_\phi)$, as derived in Chen et al. [10] and shown in Eq. 1, where the mutual information between $z^{(p)}_{(t-\Delta t:t+\Delta t)}$, $\hat{d}_t^{(p)}$ and personalized embedding, $w^{(p)}$, is $I(w^{(p)}; z^{(p)}_{(t-\Delta t:t+\Delta t)}, \hat{d}_t^{(p)})$.

$$I(w^{(p)}; z^{(p)}_{(t-\Delta t:t+\Delta t)}, \hat{d}_t^{(p)}) = H(w^{(p)}) - H(w^{(p)}|z^{(p)}_{(t-\Delta t:t+\Delta t)}, \hat{d}_t^{(p)})$$
$$\geq \mathbb{E}[log(q_\phi(w^{(p)}|z_{(t-\Delta t:t+\Delta t)}, \hat{d}_t^{(p)}))] + H(w^{(p)}) = L_I(f_{\theta,q_\phi}) \quad (1)$$

Our network is trained by combining two loss functions: one to learn the embedding, $w^{(p)}$, and one to learn the difference, $\hat{d}_t^{(p)}$, as shown in Fig. 1. L_1 minimizes the MSE between the sampled embedding approximation, $\hat{w}^{(p)}$, and the personalized embedding, $w^{(p)}$ (equivalent to maximizing the log-likelihood of the posterior). L_2 minimizes the MSE between the predicted difference, $\hat{d}_t^{(p)}$, and the true difference, $d_t^{(p)} = o_t - a_t^{(p)}$. We backpropagate the sum of these losses (Eq. 2) to learn the embedding during training such that the personalized embedding reflects the individual's feedback style. Then, at test time, we freeze the network parameters, θ, ϕ, and ϕ' and utilize this personalized embedding to inform the mapping of demonstrator feedback.

$$L_{(\theta,\phi,\phi',w)} = L_{1_{(\theta,\phi,\phi')}} + \lambda L_{2_{(\theta,\phi')}} \quad (2)$$

$$L_{1_{(\theta,\phi,\phi')}} = \frac{1}{K+1}\sum_{k=0}^{K} ||\hat{w}_k^{(p)} - w_k^{(p)}|| \quad (3)$$

$$L_{2_{(\theta,\phi')}} = ||d_k^{(p)} - \hat{d}_k^{(p)}|| \quad (4)$$

IV. Synthetic Experiment and Pilot Study

We conduct a synthetic study [37] to demonstrate MIND MELD's ability to correct for suboptimal, heterogeneous feedback. In our synthetic experiment, we create artificial Wizard-of-Oz rollouts, ground truths, and human demonstrators. We demonstrate that the embeddings learn a meaningful representation of demonstrator stylistic tendencies (Fig. 2).

We additionally conducted an IRB approved pilot study [37] to test MIND MELD's ability to learn meaningful embeddings and improve upon suboptimal corrective feedback. After recruiting 34 participants, we found that MIND MELD was able to improve corrective feedback and learn embeddings that significantly correlate with demonstrators' stylistic tendencies, i.e., the way in which they deviate from optimal ($p < .001$).

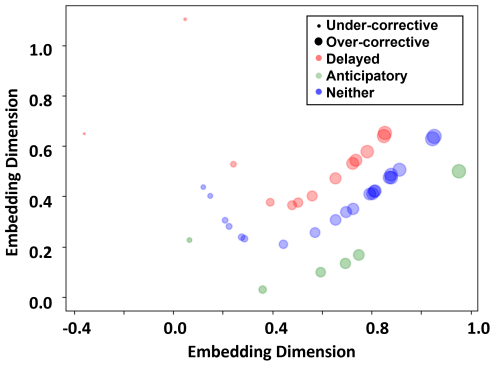


Fig. 2: This figure shows learned embeddings from our synthetic experiment. Diameter represents individuals' tendency to over-/under-correct, while color represents the tendency to provide anticipatory or delayed feedback.

Algorithm 1 MIND MELD Procedure

For M training participants, collect calibration task data
Perform gradient descent on $\theta, \phi, \phi', \omega$ until convergence (Eq. 2)
Freeze architecture parameters, ϕ, ϕ' and θ
for p in test participants **do**
  Initialize $w^{(p)} \leftarrow \frac{1}{M}\sum_{i=0}^{M} w^{(i)}$
  Collect calibration task data from p
  Perform gradient descent on ω until convergence (Eq. 4)
  Obtain initial demonstration from p.
  Present LfD algorithm conditions {MIND MELD, BC, and DAgger} in randomized order.
  for c in conditions **do**
    Train learner via condition, c, for N demonstrations.
  end for
end for

Based on results of our pilot study, we redesigned our study to better capture the stylistic tendencies of demonstrators and expanded upon our participant pool.

V. Human-Subjects Experiment

We evaluate our architecture via a human-subjects experiment with human demonstrators. Through this experiment, we demonstrate MIND MELD's ability to outperform prior LfD work by improving upon a user's suboptimal corrective feedback. Our human-subjects experiment consists of a training phase and a testing phase as discussed below. The steps comprising our study are illustrated in Algorithm 1. Our study has been approved by Georgia Tech's IRB.

Calibration Phase - In the calibration phase, we recruit participants to complete a set of calibration tasks to meta-learn the MIND MELD parameters, θ, ϕ, and ϕ' and personalized embeddings, $w^{(p)}$. Additionally, participants in this phase complete the pre-study questionnaires to capture prior experience and other demographic information.

Testing Phase - For the testing phase, we recruit a set of testing participants for a within-subjects study. These participants first complete the calibration tasks to learn their personalized embedding via Eq. 2. The participants then train

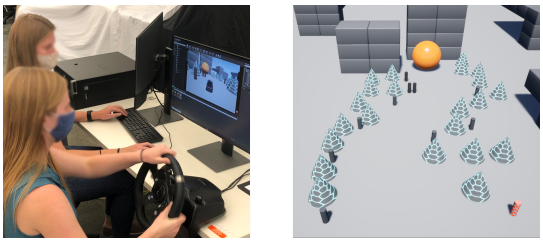


Fig. 3: The simulator and steering wheel in our human-subjects experiment are on the left and the test task is on the right.

an LfD agent via the three learning algorithms, MIND MELD, BC, and DAgger, the order of which is randomized and counterbalanced to mitigate confounding factors (e.g., fatigue, learning effects, etc.). The test task differs from the calibration tasks but is similar and falls within the same distribution (depictions of the calibrations tasks are in the Appendix). The participants in the testing phase complete both the pre-study and post-study questionnaires.

A. Driving Simulator Domain

We evaluate our approach with a human-subjects experiment in a virtual driving environment, a common domain in prior LfD, HRI, and robotics research [23], [32]. We choose to use the AirSim [40] driving simulator, an Unreal Engine-based high-fidelity physics simulator. Individuals in this experiment interact with the virtual driving environment using an Xbox steering wheel, shown in Fig. 3. We use a geometric Unreal environment where the LfD objective is to teach the agent to drive to a large, orange ball while avoiding all obstacles. The learning algorithms do not have access to the location of obstacles or the orange ball. We constrain the action space to be the position of the wheel, ranging from -540 degrees to 540 degrees. We define the state space to be composed of an image captured by a camera positioned at the front of the car as well as the car's acceleration, velocity, and position.

B. Calibration Tasks and Ground Truths

We create a series of sixteen Wizard-of-Oz [30] rollouts which are representative of successful and unsuccessful trajectories and allow us to capture the feedback styles of participants. All participants complete these tasks so MIND MELD can infer their personalized embeddings, w.

To determine ground truth optimal states for each point along the trajectories of the calibration tasks, we employ RRT* [20] (see Appendix for an example). We then apply an MPC controller along the path to determine the ground truth label at each time step.

C. Conditions

The participants first complete a set of calibration tasks which are used to learn their personalized embeddings for MIND MELD. Then, participants provide an initial demonstration from which all three agents learn an initial policy, π_0. All agents are trained for N demonstrations. Each participant experiences the following conditions in a random order.

Supervised Behavioral Cloning (BC) - Participants in this condition teach the agent via BC. To mirror our other conditions, the agent's policy is rolled out with each iteration of training so that the participant can observe the agent's behavior before providing the next demonstration.

DAgger - Participants in this condition teach the agent via vanilla DAgger [32] implemented based on prior work [22], [33]. The agent rolls out policy, π_n, and participants provide corrective feedback. The corrective labels are aggregated with the initial demonstration and corrective feedback from trials 1 to $n-1$ and the agent is retrained to yield policy, π_{n+1}.

MIND MELD (Ours) - For each demonstration, n, participants provide corrective feedback to the agent. This corrective feedback is mapped to predicted ground truth labels via MIND MELD. The mapped labels are aggregated with the initial demonstration and mapped labels from trials 1 to $n-1$ and the agent is retrained to yield policy, π_{n+1}.

D. Metrics

Below we discuss the metrics by which we evaluate MIND MELD and the learned embeddings. Both training and testing participants complete the pre-study questionnaires to determine if demographic information correlates with the learned embeddings. Only testing participants complete the post-study questionnaires. The surveys detailed below comply with the design guidelines outlined in Schrum et al. [38] and are validated from prior work when possible. The full text of the surveys and additional surveys that are not relevant to our results can be found in the Appendix. We report Cronbach's alpha (α) for each scale.

Objective Metrics

Stylistic tendencies - We analyzed participants' suboptimality by calculating their stylistic tendencies via dynamic time warping (DTW) [34] between the participant labels, a, and ground truths, o, along two-dimensions: 1) over-/under-correcting (i.e., turning the wheel too far or not enough) and 2) providing delayed/anticipatory feedback. Additional details on our calculations can be found in [37].

Goal Consistency - We measure the total number of times the agent reaches the goal, the number of demonstrations required for the agent to reach the goal, and the probability of each agent reaching the goal after each demonstration.

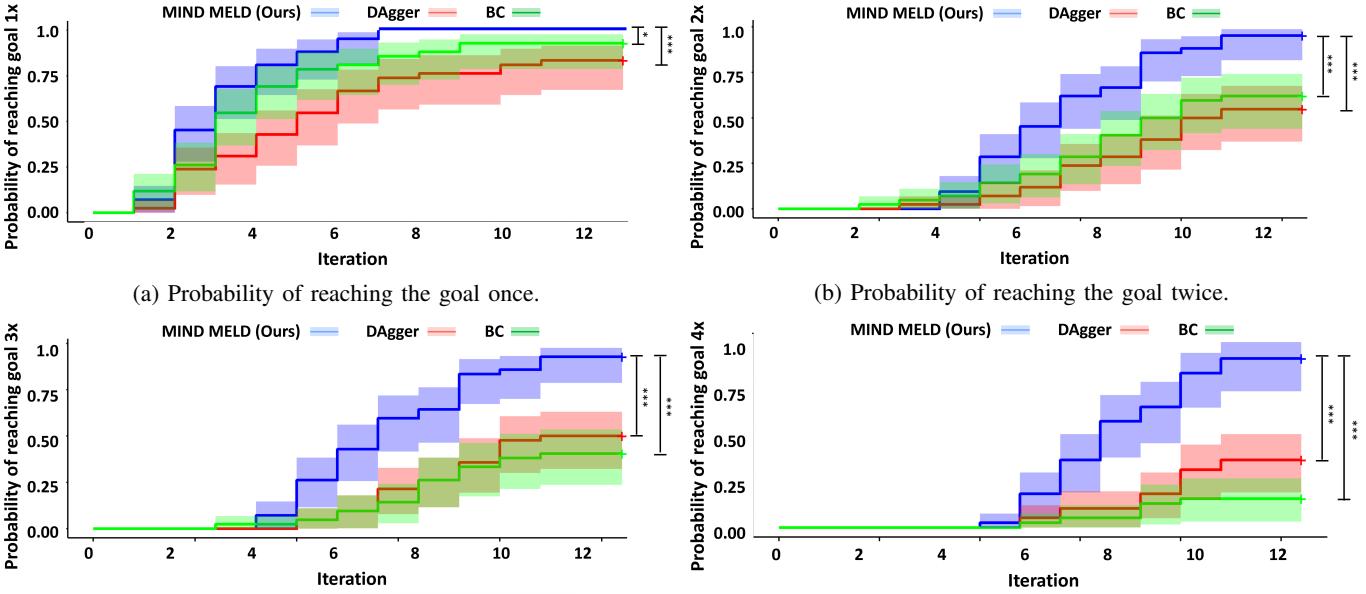
Distance - For each policy rollout of the agent, we measure the final distance between the agent and the goal.

Pre-Study Questionnaires

Prior Experience - We collect information about a participant's familiarity and experience playing video games (Cronbach's $\alpha = .93$) and driving a physical car ($\alpha = .93$) via two Likert scales to determine if prior experience correlates with the learned embeddings. Each Likert scale has eight items and a 5-point response format (strongly disagree to strongly agree). Since this survey on prior experience is ad hoc, the Appendix includes a factor analysis to validate the scales.

Post-Study Questionnaires

Trust ($\alpha = .96$) - We measure the participant's trust of the agent after each trial and for each condition [19]. In our results,



(a) Probability of reaching the goal once.

(b) Probability of reaching the goal twice.

(c) Probability of reaching the goal three times.

(d) Probability of reaching the goal four times.

Fig. 4: This figure shows that MIND MELD has a statistically significantly higher probability of reaching the goal once (Fig 4a), twice (Fig 4b), three times (Fig 4c), and four times (Fig 4d) throughout the duration of the study compared to the baselines.

we analyze the final trust survey from each condition due to the statistical testing considerations detailed in the Appendix.

Workload - We measure the workload after each condition via the NASA Task Load Index (TLX) [15].

Likeability ($\alpha = .95$) - We measure likeability after each condition via the Godspeed likeability subscale [3].

Intelligence ($\alpha = .95$) - We also measure the perceived intelligence of the agent after each condition via the intelligence subscale of Godspeed [3].

E. Procedure

An overview of our procedure for learning the MIND MELD architecture and validating MIND MELD's ability to outperform our baselines is detailed in Alg. 1. We first recruit 76 training participants by word of mouth and mailing lists. The training participants provide corrective feedback for each pre-recorded rollout which we then use to train MIND MELD and learn the parameters of MIND MELD's three subnetworks, θ, ϕ, and ϕ' as well as learn the personalized embedding, $w^{(p)}$, via Eq. 2-4. All training participants additionally answer the pre-study questionnaires.

We then recruited 42 different testing participants who experience each of the conditions discussed in Section V-C. To learn their personalized embeddings, all participants complete the calibration tasks. We then present each of the conditions discussed in Section V-C in a randomized order. All testing participants complete the pre- and post-study questionnaires.

To ensure that participants are familiar with the system before providing corrective feedback, all participants drive around in the simulator for several minutes. Additionally, participants practice providing corrective feedback in the first four calibration tasks which are not used in the training of MIND MELD so as to reduce novelty effects.

F. Hypotheses

Hypothesis 1 - *MIND MELD will improve the corrective labels provided by the participants in the calibration tasks*. We hypothesize that MIND MELD will learn to map suboptimal labels to labels that more closely approximate optimal labels by learning an embedding of stylistic tendencies of individuals.

Hypothesis 2 - *The learned embeddings will correlate with participants' stylistic tendencies and prior experience.* Based on our pilot study [37] illustrating that the learned embeddings correlated with stylistic tendencies, we predict that we will be able to reproduce these results with a larger participant pool. We also predict that the embeddings will correlate with participants' experience with video games and driving.

Hypothesis 3 - *MIND MELD will outperform DAgger and BC in terms of ability to reach goal.* We hypothesize that, due to MIND MELD's ability to correct for suboptimal feedback, MIND MELD will be more likely to reach the goal and achieve a shorter average distance from the goal.

Hypothesis 4 - *The amount by which a participant deviates from the optimal feedback style will correlate with MIND MELD's ability to outperform DAgger.* We hypothesize that participants who provide feedback that differs most from optimal (i.e., greatly over-correct) will produce poor results for DAgger. Because MIND MELD can correct for this suboptimality, the advantage of our MIND MELD algorithm over DAgger will increase with increasingly suboptimal feedback.

Hypothesis 5 - *We hypothesize that MIND MELD will achieve higher ratings on our subjective metrics compared to baselines.* Because MIND MELD corrects for suboptimality,

we hypothesize that MIND MELD will be rated higher in terms of perceived intelligence, likeability, workload, and trust.

VI. Results

We recruited 76 training participants ($M = 22.8$; $SD = 5.5$; 31.2% Female), each of whom completed the calibration tasks and filled out the pre-study questionnaires. We then recruited 42 testing participants ($M = 22.1$; $SD = 2.72$; 40% Female), each of whom completed the calibration tasks, all questionnaires, and experienced the three conditions. In our following analysis, we first determine if the data complies with parametric test assumptions before employing a parametric test. Additionally, we test each model for ordering effects and confounding factors from our covariates and find none. Specific details for all parametric testing assumptions and covariates can be found in the Appendix.

We first test if our findings support **Hypothesis 1** which predicts that MIND MELD will improve upon the corrective labels provided in the calibration tasks. We find a 55% improvement in the labels for our training participants and 37.6% improvement for our testing participants. In the Appendix, we provide graphical depictions of MIND MELD's ability to correct for suboptimal trajectories.

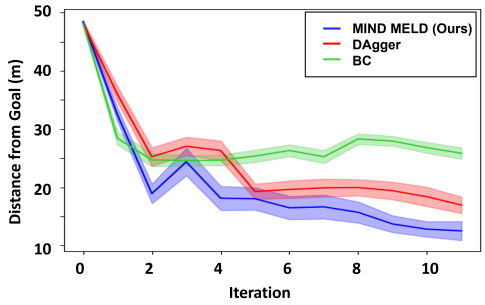


Fig. 5: This figure shows the average distance and standard deviation from the goal for each algorithm after each iteration. At each iteration, the agent rolls out the current policy and the participant provides a demonstration.

To test **Hypothesis 2**, we conduct a correlation analysis between the learned embeddings and the results of our dynamic time warping describing participants' over-/under-correcting and delayed/anticipatory tendencies. We find support for the results in our pilot study and find that the learned embeddings significantly correlate with participants' tendency to over-/under-correct ($r(116) = -.47, p < .001$) and provide anticipatory/delayed feedback ($r(116) = .49, p < .001$). To further investigate **Hypothesis 2** and determine if prior experience correlates with the learned embeddings, we conduct a correlation analysis between experience with driving and experience with video games. We find that experience with video games significantly correlates with the learned embedding ($\rho = .19, p = .038$).

To investigate **Hypothesis 3**, we next analyze the ability of each agent to reach the goal, in terms of both probability and frequency, over the course of the study. To determine the probability of reaching the goal at each iteration, we conduct a survival analysis, a statistical technique commonly used in medical research to assess the expected time until an event takes place [13]. Survival analysis allows us to analyze data for which an event may never occur. For example, an agent may never reach the orange ball during the study, yet we can still include this data in our survival analysis as "censored" data. In our study, time corresponds to the number of demonstrations that the agent has experienced. An event occurs when the agent reaches the goal the specified number of times.

	MELD-DAgger	MELD-BC	DAgger-BC
Workload	-8.1 (2.8) $p = .005$	-10.0 (2.8) $p < .001$	-2.0 (2.9) $p = .87$
Likeability	1.1 (.25) $p = .004$	1.4 (.28) $p = .001$	.31 (.27) $p = .37$
Intelligence	1.2 (.32) $p = .008$	1.7 (.31) $p < .001$	.53 (.31) $p = .35$
Trust	0.80 (.16) $p < .001$	1.1 (.14) $p < .001$	0.32 (.14) $p = .192$
Distance	-4.5 (.88) $p < .001$	-7.7 (.80) $p < .001$	-3.2 (.82) $p = .01$

TABLE I: We report the means (standard deviations) of the difference between the agents and associated p-values for objective and subjective metrics.

Fig. 4 shows the Kaplan-Meier curves for reaching the goal once, twice, three times, and four times. We find that MIND MELD is statistically significantly more likely to reach the goal once (log rank $p < .001$), twice (log rank $p < .001$), three times (log rank $p < .001$), and four times (log rank $p < .001$) throughout the course of the study compared to DAgger and BC. We find that MIND MELD has a 100% chance of reaching the goal once after the seventh iteration whereas the baselines never achieve 100% probability of reaching the goal even once. Likewise, we find that MIND MELD has a $> 80\%$ chance of reaching the goal three times after the ninth iteration whereas the baselines have a $< 50\%$ chance. This result supports **Hypothesis 3** and shows MIND MELD learns a better policy in terms of probability of reaching the goal.

We additionally apply a Poisson regression with a Tukey post hoc to determine if there is a statistically significant difference between the total number of times that each agent reaches the goal throughout the study. We find that MIND MELD reached the goal 2.1x more than DAgger ($p < .001$) and 2.6x more than BC ($p < .001$).

Next, we analyze the average distance from the goal across iterations for each algorithm. We conduct a repeated measures ANOVA with a Tukey post hoc comparing the distance to the goal for each condition. As shown in Table I, we find that MIND MELD achieved a statistically significantly lower average distance from the goal ($M = 20.4, SD = 5.58$) compared to DAgger ($M = 24.8, SD = 5.92, p < .001$) and BC ($M = 28.2, SD = 4.86, p < .001$). Fig. 5 shows the average distance to the goal for each trial and condition. Note that a trial ends after the agent either reaches the orange ball or crashes into an obstacle.

To determine if our findings support **Hypothesis 4**, we conduct a correlation analysis between the participants' stylistic tendencies and the average performance difference between MIND MELD and DAgger. We find that participants' delayed/anticipatory tendencies significantly correlate with MIND MELD's advantage over DAgger ($r(40) = .36$, $p = .017$), as shown in Fig. 6.

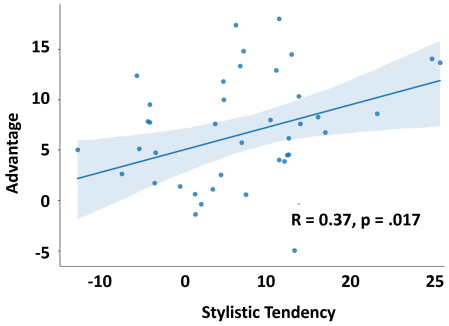


Fig. 6: This figure shows a plot of participants' tendency to provide delayed/anticipatory feedback vs. the difference between the average performance of MIND MELD and DAgger.

We lastly investigate our findings in the context of **Hypothesis 5** to determine if MIND MELD is rated subjectively higher by participants. We conducted a repeated measures ANOVA with a Tukey post hoc or Friedman's test (see omnibus statistics in the Appendix). As shown in Table I, MIND MELD is rated statistically significantly higher compared to both DAgger and BC for all subjective metrics. These findings support **Hypothesis 5**.

VII. Discussion

In our analysis, we find support for **Hypotheses 1-5**, illustrating that MIND MELD can learn stylistic tendencies of suboptimal and heterogeneous demonstrators, map the suboptimal feedback to better feedback, and, as a result, outperform prior work in both robot-centric and human-centric LfD. We find that MIND MELD is able to learn various participant styles, such as participants' tendency to over-/under-correct ($p < .001$) and provide delayed and anticipatory feedback ($p < .001$), suggesting that MIND MELD can provide positive results with a diverse user pool. For more discussion on stylistic tendencies, please refer to the Appendix.

Because MIND MELD is able to learn heterogeneous tendencies and utilize this information to correct for suboptimal behavior, we find that MIND MELD outperforms prior work in terms of its ability to reach the goal in an LfD task. MIND MELD achieves both a higher probability of reaching the goal and a lower average distance from the goal compared to both baselines, DAgger ($p < .001$) and BC ($p < .001$). Additionally, we observe that the more delayed a participant is at providing feedback, the better MIND MELD performs over DAgger ($p = .017$). We find that, for participants who provide less suboptimal feedback, MIND MELD and DAgger exhibit more similar performance because there is less of a need to correct a participants' feedback. When a participant's behavior deviates more from the optimal, DAgger performs worse, whereas MIND MELD is able to correct for the suboptimality.

Not only do we see improved performance in terms of objective metrics, we also find that MIND MELD outperforms both DAgger and BC in terms of our subjective metrics. Participants rate MIND MELD to be more likeable ($p = .004$), intelligent ($p = .008$), and trustworthy ($p = .001$) compared to DAgger. Additionally, we find the participants' perceived workload is rated as lower for MIND MELD ($p = .005$). This is an interesting finding considering that for both MIND MELD and DAgger, participants are tasked with providing corrective feedback to the agent. With respect to performance and human usability, MIND MELD achieves the best of both worlds. MIND MELD improves upon the performance of robot-centric algorithms, while being easy to teach, likeable, intelligent, and trustworthy.

VIII. Limitations/Future Work

Due, in part, to the recruiting difficulties imposed by the COVID-19 pandemic, our sample population consisted primarily of students with a mean age of 22.6. In the future, we plan to conduct this experiment with a more diverse set of participants. We also note that MIND MELD requires training participants to meta-learn the model parameters and a set of calibration tasks with ground-truth labels to learn the personalized embeddings. However, our results demonstrate that MIND MELD improves the quality of the corrective feedback by 37.6% and LfD outcomes ($p < .001$), making this additional step worthwhile.

Additionally, MIND MELD makes several assumptions, listed in Section III, about the way in which individuals provide corrective feedback. Yet, the success of our algorithm suggests that these assumptions appear to be sufficiently met for our experimental setup. For this study, we assume that a person's feedback style will remain constant; however, we do expect that, over a longer period of interaction, a person's style of feedback may change and adapt. In future work, we plan to investigate how to update our framework to account for and learn changing styles during longitudinal LfD.

Lastly, we aim to investigate if we can replicate the benefits of MIND MELD in other domains. We plan to implement MIND MELD on a robot arm domain, which may produce different behavior and stylistic tendencies amongst participants due to more degrees of freedom and a more complex user interface.

IX. Conclusion

We introduce MIND MELD, a novel LfD framework that learns personalized embeddings from heterogeneous users and improves upon suboptimal human feedback for robot-centric LfD algorithms. Through a human-subjects experiment, we showed that MIND MELD outperforms a human-centric baseline, BC, and a robot-centric baseline, DAgger, with regards to multiple measures of algorithm performance. Furthermore, users found MIND MELD more intelligent, likeable, trustworthy, and easier to teach than BC and DAgger.

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