Improving Robot-Centric Learning from Demonstration via Personalized Embeddings

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Abstract

Learning from demonstration (LfD) techniques seek to enable novice users to teach robots novel tasks in the real world. However, prior work has shown that robot-centric LfD approaches, such as Dataset Aggregation (DAgger), do not perform well with human teachers. DAgger requires a human demonstrator to provide corrective feedback to the learner either in real-time, which can result in degraded performance due to suboptimal human labels, or in a post hoc manner which is time intensive and often not feasible. To address this problem, we present Mutual Information-driven Meta-learning from Demonstration (MIND MELD), which meta-learns a mapping from poor quality human labels to predicted ground truth labels, thereby improving upon the performance of prior LfD approaches for DAgger-based training. The key to our approach for improving upon suboptimal feedback is mutual information maximization via variational inference. Our approach learns a meaningful, personalized embedding via variational inference which informs the mapping from human provided labels to predicted ground truth labels. We demonstrate our framework in a synthetic domain and in a human-subjects experiment, illustrating that our approach improves upon the corrective labels provided by a human demonstrator by 63%.

1 Introduction

In Learning from Demonstration (LfD), a robot seeks to perform a task by observing human task demonstrations [Ardagni et al. 2009]. In human-centric LfD, the human demonstrator drives the interaction and provides the demonstrations for each trajectory. In robot-centric LfD, a demonstrator observes the robot and must provide corrections to the robot learner for the learner to gather new information and improve upon its current policy [Laskey et al. 2017]. One such example of human-centric learning is Behavioral Cloning (BC) in which the demonstrator provides a series of demonstrations and the agent is trained via supervised learning. BC, however, suffers from covariate shift and performs poorly when the environment’s transition dynamics are stochastic [Ross and Bagnell 2010; Osa, Neumann, and Peters 2018]. To overcome this limitation, Ross, Gordon, and Bagnell [2011] introduced a robot-centric approach, called Dataset Aggregation (DAgger). DAgger learns a policy, \( \pi_0 \), from the initial trajectories provided by the demonstrator. \( \pi_0 \) is then rolled out and the demonstrator provides corrective feedback. The new, corrective labels provided by the demonstrator are aggregated with the previous trajectories and used to train a new policy.

Prior work in robot-centric LfD has shown that DAgger outperforms human-centric LfD algorithms, such as BC, when the demonstrator is an oracle that provides high-quality labels (Ross, Gordon, and Bagnell 2011). However, such studies do not necessarily translate to the real-world with human demonstrators (Amershi et al. 2014; Spencer et al. 2020; Berggren 2019). Prior work by Laskey et al. (2017) has shown that DAgger performs poorly and may even perform worse than BC when the demonstrator is a human and the learner is a neural network. DAgger’s poor performance is due to the fact that humans often provide poor quality feedback (Sena and Howard 2020). Furthermore, humans differ in the way they provide this feedback depending on the task and the human’s abilities (Sammut 1992; Paleja and Gombolay 2019). This suboptimality and heterogeneity can make it difficult for robots to learn from human teachers. To effectively learn from a human demonstrator, robot-centric LfD approaches must take into account a teacher’s demonstration style to correct for the teacher’s suboptimality and improve the policy of the learner. Yet, no prior work has investigated correcting for demonstrator suboptimality while accounting for heterogeneity among demonstrators.

To overcome this limitation, we introduce Mutual Information-driven Meta-learning from Demonstration (MIND MELD), which meta-learns an individual-specific mapping from human labels to predicted ground truth labels via a Long Short-Term Memory (LSTM) based neural network architecture. Because individuals differ in the way that they provide feedback, we propose to learn a personalized embedding via variational inference that encapsulates information about individual tendencies and corrective styles. This personalized embedding informs the mapping of an individual’s suboptimal labels to labels that more closely approximate the ground truth, thus improving upon the performance of robot-centric LfD methods for DAgger-based training.

To evaluate the ability of MIND MELD to learn meaningful embeddings and improve upon human-provided, subop-
timal corrective labels, we conduct a human-subjects study in which we recruit human demonstrators to provide corrective feedback to an agent. Additionally, we investigate if the learned personalized embeddings capture salient aspects of demonstrator style via correlation analysis between the learned embeddings, stylistic tendencies, personality traits, and experience metrics.

In our work, we contribute the following:

1. We create a novel, personalized learning from demonstration framework, MIND MELD, for inferring individual demonstrator styles and improving upon suboptimal corrective labels.

2. We conduct a human-subjects study in which participants provide corrective feedback in a series of tasks to train MIND MELD.

3. We present results that demonstrate the ability of MIND MELD to improve upon suboptimal human labels and learn meaningful representations of demonstrator style. We show that MIND MELD is able to improve suboptimal human-provided labels by 63% by inferring personalized embeddings. We demonstrate that these embeddings significantly correlate with stylistic tendencies of the demonstrator ($p < .001$).

2 Related Works

Prior work has investigated supervised learning approaches to learn a mapping function from states to actions based on trajectories provided by an expert demonstrator (Chernova and Veloso 2009; Ross, Gordon, and Bagnell 2011; Ravichandar et al. 2020; Liu, Gombolay, and Balakirsky 2021). The problem encountered when learning this mapping is that the independent and identically distributed (i.i.d.) assumption is violated because the learner’s predictions affect future states (Ross and Bagnell 2010; Jena, Liu, and Sycara 2020) and the number of mistakes the learner makes is quadratically proportional to the horizon time, $T$.

To address this problem, Ross et al. introduced Dataset Aggregation (DAgger) which aggregates a training set based on expert labels queried during a policy rollout instead of relying on a mixture of previous policies (Ross, Gordon, and Bagnell 2011). DAgger utilizes the state distribution induced by the current policy to request labels from the expert and a gating function determines the mixture of expert and learner during each rollout. The authors of this work prove similar linear loss guarantees to prior work and show that DAgger empirically outperforms prior work.

While DAgger performs well when quality expert labels are provided, Laskey et al. (2017) demonstrated that robot-centric learning approaches such as DAgger can result in mislabelling and therefore poor performance of the learner. The authors show that human-centric learning, in which the expert demonstrates the task to the learner, can actually outperform DAgger. Additionally, DAgger suffers from the high work load it places on the demonstrator which can result in expert fatigue and poor results (Kelly et al. 2019; Laskey et al. 2016; Packard and Onta 2018). Furthermore, it can be impractical for humans to provide corrective feedback to DAgger in real-time (Ross et al. 2013).

To overcome this challenge posed by robot-centric LfD, prior work has attempted to relieve the burden placed on the expert by DAgger and improve upon the interaction with the learner (Daume and Eisner 2012; Kelly et al. 2019; Spencer et al. 2020; Menda, Driggs-Campbell, and Kochenderfer 2019). Daume et al. proposed an imitation learning by coaching algorithm in which the coach gradually provides more and more difficult actions for the learner to imitate (Daume and Eisner 2012). The coach demonstrates actions that are preferred by the learner, meaning they induce a lower task loss. Results show that such a coaching scheme is able to outperform DAgger and achieve a lower regret bound. To reduce the workload of the expert and improve upon the provided demonstrations, Kelly et al. proposed HG-DAgger which allows the expert to operate the gating function, meaning that the expert decides when to be in control and when to passively observe the learner (Kelly et al. 2019). This alleviates the difficulty of providing accurate labels and consequently learns a stationary policy which stabilizes around the expert trajectories. Spencer et al. expands on this idea and utilizes both expert interventions and non-interventions to learn a policy in the Expert Intervention Learning (EIL) algorithm (Spencer et al. 2020).

While prior work has learned LfD policies from heterogeneous demonstrators (Paleja et al. 2021) and attempted to improve upon DAgger by handing control back to the human (Kelly et al. 2019), our approach is the first to improve upon robot-centric learning by inferring demonstrator style. Additionally, there is a need for LfD algorithms that can effectively learn from suboptimal and heterogeneous demonstrators (Ravichandar et al. 2020).

3 Methodology

In this section, we discuss our methodology for improving upon robot-centric learning from demonstration. We first outline our network architecture and learning scheme for personalized embeddings and label mapping. We next describe our simulated experiment for proof-of-concept and to verify our network architecture in Section 4. Lastly, we describe our human-subjects experiment with humans as demonstrators in Section 5.

3.1 Preliminaries

We frame the LfD problem as a Markov Decision Process (MDP) $\mathcal{R}$. The MDP $\mathcal{R}$ is defined by the 4-tuple $\langle \mathcal{S}, \mathcal{A}, T, \gamma \rangle$. $\mathcal{S}$ 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 $a$. $\gamma$ 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 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.

3.2 Assumptions

In our methodology, we make the following assumptions.
We utilize the bi-directional LSTM, consisting of three components: 1) The bidirectional LSTM encoder, \( E_{\phi'}: A \rightarrow Z \), 2) the prediction subnetwork, \( f_\theta: Z \times W \rightarrow \mathbb{R} \), and 3) the mutual information subnetwork, \( g_\phi: Z \times \mathbb{R} \rightarrow N_W \). The label that we are trying to improve upon is designated as \( a_{t',p}(p) \) for demonstrator, \( p \), where \( t' \in (t, t + \Delta t) \). \( Z \subseteq \mathbb{R}^k \) is the set of \( k \)-dimensional encodings extracted from the sequence of corrective feedback. We utilize the bi-directional LSTM, \( E_{\phi'} \), to extract an encoding, \( \hat{z} \in Z \), for the sequence of corrective labels, \( a_{(t:t+\Delta t)}(p) \), provided from time \( t \) to \( t + \Delta t \) by person \( p \).

\( W = \{ w^1, w^2, \ldots w^p \} \subseteq \mathbb{R}^d \) is the set of \( d \)-dimensional personalized embeddings. \( f_\theta \) maps the encoding, \( \hat{z} \), and personalized embedding, \( \hat{w}^{(p)} \), to the predicted difference, \( d_{t'}^{(p)} \in \mathbb{R} \), between the ground truth label, \( o_{t'} \), and the individual’s corrective label, \( a_{t'}^{(p)} \). Because we train \( g_\phi \) to maximize the log-likelihood as discussed in the next section, this subnetwork recovers a multivariate normal distribution, \( N_W \) (Paleja and Gombolay 2019). Specifically, this subnetwork learns a mapping of the encoding, \( \hat{z} \), and predicted difference, \( d_{t'}^{(p)} \), to a normal distribution (representing the posterior distribution) of the demonstrator’s personalized embedding, \( \hat{w}^{(p)} \). We initialize \( w^{(p)} \) based upon the prior, \( \hat{w}^{(p)} \sim N(0, 1) \), and sample from the approximate posterior to produce \( \hat{w}^{(p)} \), representing an estimate of the embedding.

3.3 Architecture

Fig. 1 shows our network architecture. Our architecture consists of three components: 1) The bidirectional LSTM encoder, \( E_{\phi'}: A \rightarrow Z \), 2) the prediction subnetwork, \( f_\theta: Z \times W \rightarrow \mathbb{R} \), and 3) the mutual information subnetwork, \( g_\phi: Z \times \mathbb{R} \rightarrow N_W \). The label that we are trying to improve upon is designated as \( a_{t',p}(p) \) for demonstrator, \( p \), where \( t' \in (t, t + \Delta t) \). \( Z \subseteq \mathbb{R}^k \) is the set of \( k \)-dimensional encodings extracted from the sequence of corrective feedback. We utilize the bi-directional LSTM, \( E_{\phi'} \), to extract an encoding, \( \hat{z} \in Z \), for the sequence of corrective labels, \( a_{(t:t+\Delta t)}(p) \), provided from time \( t \) to \( t + \Delta t \) by person \( p \).

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3.4 Variational Inference

In this work, we are motivated by the assumption that humans exhibit various and distinct styles when providing corrective feedback. Therefore, to accurately correct for suboptimal demonstrations, we encapsulate information about the individual’s corrective style via a personalized embedding, \( \hat{w}^{(p)} \), for individual, \( p \), as described in Eq. 1. In our formulation, we want to maximize mutual information between our learned personalized embedding, \( \hat{w}^{(p)} \), the encoding of the demonstrator labels, \( \hat{z} \), and corrective mapping, \( d_{t'}^{(p)} \), to ensure that our embeddings are capturing the salient information about the demonstrator’s style. Intuitively, maximizing mutual information means that observing informa-
tive corrective feedback should reduce the uncertainty of our learned embedding.

Because maximizing the mutual information requires access to an intractable posterior distribution, \( P(\vec{w}^{(p)}|\vec{z}, \vec{d}_t^{(p)}) \), we employ variational inference and the evidence lower bound to reach a solution as shown in Eq. 1. Further details on the derivations can be found in Chen et al. (2016). Via this formulation, we thus encourage \( \vec{w} \) to encapsulate salient information about the demonstrator’s style. The mutual information between \( \vec{z}, \vec{d}_t^{(p)} \) and personalized embedding, \( \vec{w}^{(p)} \), is denoted as \( I(\vec{w}^{(p)}; \vec{z}, \vec{d}_t^{(p)}) \). The variational lower bound is \( L_1(f_{\theta|\vec{w}}, g_{\phi|\theta}) \).

\[
I(\vec{w}^{(p)}; \vec{z}, \vec{d}_t^{(p)}) = H(\vec{w}^{(p)}|\vec{z}, \vec{d}_t^{(p)}) - H(\vec{w}^{(p)}) \geq \mathbb{E}[\log(g_{\phi}(\vec{w}^{(p)}|\vec{z}, \vec{d}_t^{(p)}))] + H(\vec{w}^{(p)}) = L_1(f_{\theta|\vec{w}}, g_{\phi|\theta})
\]

We utilize two separate loss functions to train our network to learn both the embedding, \( \vec{w}^{(p)} \), and the difference, \( \vec{d}_t^{(p)} \), as shown in Fig. 1. We minimize the mean squared error between the sampled embedding approximation, \( \vec{w}^{(p)} \), and the personalized embedding, \( \vec{w}^{(p)} \), which is equivalent to maximizing the log-likelihood of the posterior. We also minimize the mean squared error between \( \vec{d}_t^{(p)} \) and the difference between the ground truth embedding, \( o_t \), and \( a_t^{(p)} \). These losses are summed (Eq. 2), and are backpropagated through the layers and the input embedding, \( \vec{w}^{(p)} \), to update and learn the embedding during training. Therefore, during training, the personalized embedding will eventually converge to reflect the individual’s feedback style. During test time, this personalized embedding informs the mapping of new feedback to improved labels.

\[
L_{\theta, \phi, \phi', \vec{w}} = \frac{1}{K+1} \sum_{k=0}^{K} \left( (\hat{w}_k^{(p)} - \vec{w}_k^{(p)})^2 + (d_k^{(p)} - (a_k^{(p)} - o_k))^2 \right)
\]

4 Synthetic Experiment

Before evaluating MIND MELD on human demonstrators, we first conduct a synthetic experiment to fine-tune the architecture and evaluate MIND MELD’s ability to correct for suboptimal labels. To do so, we simulate a driving task in which the objective of the demonstrator is to teach the agent to drive to a goal location in the environment. The state space is defined as the position of the car and the continuous action space is defined as the angle of the wheel. We assume that turning the wheel \( \Delta \theta \) causes the car to turn by an equivalent amount.

To create synthetic training data by which to train our architecture, we first create a set of artificial DAgger-like roll-outs (Fig. 2b). The ground truth labels are calculated as the difference in the heading of the agent and the angle to the goal (Fig. 2c). We create a set of artificial, suboptimal demonstrators by randomly assigning each demonstrator either a delayed (actions are executed later in time compared to the ground truth), anticipatory (actions are executed sooner in time compared to the ground truth), or neither style (actions temporally match the ground truth) and to be either an over-corrector (actions are greater in magnitude

Figure 2: This figure shows the creation of the synthetic data. a) shows the artificial DAgger rollouts, b) the ground truth labels, c) the demonstrators, and d) the corrective feedback. The mapping of suboptimal labels via our architecture, MIND MELD, produces embeddings shown in f). In f), the diameter of a point represents the degree to which an individual over- or under-corrects. The color represents the individual’s style (i.e., delayed, anticipatory, or neither).
compared to the ground truth) or under-corrector (actions are smaller in magnitude compared to the ground truth) by a randomly selected magnitude (Fig. 2). This “style” is then utilized to map the ground truth labels to suboptimal, artificial human labels (Fig. 2). We employ this artificial data to demonstrate the ability of our architecture to correct for poor human labels.

4.1 Results

Fig. 2 shows the results of the learned embeddings plotted in latent space. The embeddings for individuals that greatly over-correct are clustered towards the right of the graph and those that greatly under-correct are located towards the left. Those who neither over-correct nor under-correct are located at the elbow in the plot. Additionally, those who provided delayed feedback are located towards the top of the plot and those who provided anticipatory feedback are located towards the bottom. These results confirm that our embeddings learn meaningful representations of an individual’s feedback style. Furthermore, we confirm that our architecture successfully maps the suboptimal feedback to feedback that is closer to the ground truth embeddings. We find a 61% improvement of labels in the calibration tasks. For unseen test tasks that are not used to train our network, we find a 55% improvement in the quality of the labels after mapping. These results show that Mind Meld is able to learn meaningful personalized embeddings and utilize these embeddings to improve upon suboptimal corrective feedback.

5 Human-Subjects Experiment

We conduct a human-subjects experiment to evaluate our architecture with human demonstrators and illustrate Mind Meld’s ability to improve upon suboptimal corrective feedback. Our study has been approved by the IRB under protocol H19630.

5.1 Driving Simulator Domain

We evaluate Mind Meld in a driving simulation domain with human demonstrators, a common task in prior LfD work (Laskey et al., 2016; Ross, Gordon, and Bagnell, 2011). We employ the AirSim driving simulator based on Unreal Engine in conjunction with an Xbox steering wheel and pedals, shown in Fig. 3. We utilize a simple Blocks environment in which the objective of the LfD task is to drive to a large orange ball. The state space is defined as the position, body velocity, body acceleration of the car, and the image provided by the camera located on the front of the car. The action space is the position of the wheel and is constrained to be between -2.5 to 2.5.

We create a series of twelve synthetic, DAgger-like rollouts, an example of which is shown in Fig. 4. These rollouts are representative examples of DAgger rollouts that allow us to capture the feedback styles of participants. The 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, $\theta$, $\phi$, and $\phi'$ as well as learn the personalized embedding, $\vec{w}(p)$.

Before providing corrective feedback, participants were given the opportunity to drive in the environment and familiarize themselves with the controls to mitigate learning effects and stabilize performance.

5.2 Ground Truth Data

To determine ground truth optimal states for the calibration tasks, we employ RRT* as shown in Fig. 4. At each point along each calibration task trajectory, we determine the optimal path to the goal via RRT*. We then apply a Stanley controller to the path to determine the ground truth label at each point in time.

5.3 Participants

We recruit 34 training participants via mailing lists and word of mouth. Each of these participants provide corrective demonstrations for the calibration tasks which are utilized to train the Mind Meld architecture.

5.4 Metrics

Below we discuss the metrics by which we evaluate Mind Meld and the learned embeddings. All survey responses are collected at the beginning of the experiment. All surveys comply with the design guidelines specified in Schrum et al. (2020) and are validated in prior work if possible.

Big Five Personality Survey - We collect information about the participant’s personality via the Mini-IPIP questionnaire (Cooper, Smillie, and Corr, 2010) to determine if personality correlates with the learned embedding.
**Prior Experience** - We collect information about a participant’s familiarity and experience playing video games, driving a physical car, and driving a virtual car via three Likert scales. Each Likert scale has 8 items and a 7-point response format (strongly disagree to strongly agree). We aim to determine whether prior experience with video games or driving correlates with the learned embedding.

**Trust in Automation** - We measure the participant’s trust in automation via the survey presented in [Adams et al. 2003].

**Stylistic tendencies** - We analyzed participants’ tendency to either over-correct (i.e., turn the steering wheel too far) or under-correct (i.e., turn the steering wheel not enough) as well as provide delayed or anticipatory feedback via dynamic time warping (DTW) (Salvador and Chan 2004) between the participant labels, $a$, and ground truth, $o$. To estimate the difference in amplitude between the $a$ and $o$ signals, we used DTW to match up the signals in time and calculated the distance, $D_k$, between each time point using the Euclidean distance, $d$. We then summed the distances along the DTW path. To account for whether a participant was over- or under-correcting, we considered whether $a$ or $o$ had a larger magnitude (Eq. 3).

$$D = \sum_{k=0}^{\infty} (-1)^x d(a_k, o_k)$$

where:

$$x = \begin{cases} 
0 & \text{if } a_k > 0 \text{ and } a_k \geq o_k \\
1 & \text{if } a_k > 0 \text{ and } a_k < o_k \\
1 & \text{if } a_k < 0 \text{ and } a_k \geq o_k \\
0 & \text{if } a_k < 0 \text{ and } a_k < o_k 
\end{cases}$$

(3)

To determine whether a participant was providing delayed or anticipatory feedback, we determined the number of timesteps between $a$ and $o$ on the DTW path. If the majority of points in $a$ were matched to later points in $o$, then our metric for timing was valued as negative or anticipatory; otherwise, our metric was positive or delayed. This analysis provided insight into the participants’ stylistic tendencies and allowed us to determine if the learned embeddings correlated with these stylistic tendencies.

5.5 Hypotheses

**Hypothesis 1** - MIND MELD will improve the corrective labels provided by the participants in the calibration tasks. We hypothesize that MIND MELD will be able to sufficiently capture the stylistic tendencies of the participants and, based upon these learned embeddings, map the suboptimal labels to labels that more closely approximate the ground truth.

**Hypothesis 2a** - The learned embeddings will correlate with personality traits. We hypothesize that personality traits will inform an individual’s corrective style. Therefore, we will find a correlation between the individual’s personality and their learned embedding.

**Hypothesis 2b** - The learned embeddings will correlate with experience playing video games. We hypothesize that individuals with more video game experience will provide corrective feedback that more closely approximates optimal feedback, which would be reflected in the personalized embedding.

**Hypothesis 2c** - The learned embeddings will correlate with driving experience. We hypothesize that those who often drive cars will find the virtual car and corrective feedback to be counter-intuitive due to the fact that the car does not actually respond to their feedback. Therefore, we expect to see a correlation between experience driving cars and the learned embeddings.

**Hypothesis 3a** - The learned embeddings will correlate with participants’ tendency to over- or under-correct. Over- and under-correcting are prominent stylistic tendencies that we observed in pilot participants. Thus, we hypothesize that the learned embeddings will encapsulate an individual’s tendency to over- or under-correct and correlate with this tendency.

**Hypothesis 3b** - The learned embeddings will correlate with participants’ tendency to provide delayed or anticipatory feedback. We observed that pilot participants tended to either provide feedback that was delayed or anticipatory. Therefore, we hypothesize that the embeddings will correlate with the amount by which the participant provides delayed or anticipatory feedback.

| Survey       | Mean  | Standard Dev | Cronbach’s α |
|--------------|-------|--------------|--------------|
| Video Games  | 30.8  | 11.9         | 0.90         |
| Virtual Cars | 28.8  | 10.0         | 0.91         |
| Physical Cars| 36.7  | 11.9         | 0.93         |
| Trust        | 64.3  | 7.0          | 0.59         |
| Extraversion | 13.3  | 5.9          | 0.84         |
| Agreeableness| 20.4  | 3.8          | 0.67         |
| Conscientiousness| 20.4 | 3.6       | 0.90         |
| Neuroticism  | 9.2   | 5.5          | 0.78         |
| Openness     | 18.4  | 5.2          | 0.80         |

Table 1: We report average score and Cronbach’s α for each survey.

6 Results

We recruited 34 participants (Mean age: 28; Standard deviation: 11.9; 29.4% Female), each of whom completed the calibration tasks and filled out the questionnaires. The mean score and internal consistency for each questionnaire is reported in Table 1. We trained MIND MELD on the participant data and learned each participant’s personalized embedding. To train our architecture, we employed Pytorch 3.7 with a learning rate of 0.001. We found that we were able to improve participant corrective labels by 63% on a hold-out calibration task. This result supports Hypothesis 1 and suggests that MIND MELD was able to learn the stylistic tendencies encapsulated in the embeddings as well as learn how to improve upon suboptimal labels given a participant’s learned embedding.

To determine if the learned embeddings correlate with constructs of interest, we performed a correlation analysis between the learned embeddings and participants’ experi-
en, personality traits, and stylistic tendencies. To determine if our data is normally distributed and homoscedastic, we conducted Shapiro-Wilk’s test and the non-constant variance score test, respectively. If the data did not pass the assumption checks, we employed Spearman’s test. Otherwise, we used Pearson’s test. The results of the correlation analysis between the learned embedding and the construct are reported in Table 2. We found participants’ stylistic tendencies (i.e., their tendency to over- or under-correct and provide delayed and anticipatory feedback) to be significantly correlated with the learned embeddings. This finding shows that MIND MELD is able to learn a meaningful representation of participants’ demonstration styles and supports our Hypotheses 3a and 3b. While we did not find significance at the α = .05 level for experience surveys, experience with virtual cars and physical cars are trending towards significance with p-value of .18 and .15, respectively. Although we do not claim that these results support our hypotheses, since we do not find significance below the α = .05 level, this finding suggests that participants who have more experience operating virtual cars or physical cars may provide stylistically different feedback than those who do not. Similarly, we find that the personality trait for neuroticism is trending towards significance (p-value of .16) suggesting that how a person deals with stress may impact their style of providing feedback. We additionally performed a t-test to determine if gender significantly affected the value of the learned embeddings. We found that gender was significant for predicting the learned embeddings with p = .0015.

The relationships we observe between demographic information, stylistic tendencies, and the embedding space suggest that MIND MELD is able to learn meaningful differences between heterogeneous demonstrators. An exploration of what it means to be more “female” or more of an “over-corrector” in the context of the embedding space is out of the scope of this paper and, therefore, we do not comment on the meaning of these correlations. Advances in explainable AI may allow us to further explore the meaning behind these correlations in future work.

Our main findings are the following:

• MIND MELD improves upon suboptimal, human-provided corrective labels by 63%.
• The learned embeddings significantly correlate with demonstrator stylistic tendencies (p < .001).
• The learned embeddings significantly correlate with demonstrator gender (p = .0015).
• Participants’ experience with virtual cars, (p = .18), physical cars (p = .15) and neuroticism (p = .16) trend towards significance.

7 Limitations/Future Work

MIND MELD is limited by the fact that training participants are required to learn the personalized embeddings and that we have access to ground truth labels for the calibration tasks. However, our results demonstrate that MIND MELD improves the quality of the corrective feedback and LfD outcomes, making this additional step a worthwhile endeavor. Additionally, MIND MELD makes several assumptions, as listed in Section 3, about the way in which individuals provide corrective feedback. Yet, the success of our algorithm suggests that these assumptions hold for our purposes.

Because MIND MELD requires ground truth labels in the calibration tasks, we are assuming there is one optimal solution to the task (i.e., teach the car the shortest path to the goal). However, some domains may allow for diverse demonstrations and solutions. For example, in autonomous driving, one person might prefer to take the scenic route, while another would prefer the fastest route. In this work, we investigate heterogeneity of feedback style, but not the heterogeneity of multiple task solutions. In future work, we

| Metric          | Correlation | p-value |
|-----------------|-------------|---------|
| Video Games     | 0.19        | .28     |
| Virtual Cars    | 0.24        | .18     |
| Physical Cars   | -0.25       | .15     |
| Trust           | -0.06       | .75     |
| Extraversion    | -0.21       | .22     |
| Agreeableness   | 0.14        | .43     |
| Conscientiousness| -0.033     | .89     |
| Neuroticism     | 0.25        | .16     |
| Openness        | 0.17        | .34     |
| Over-/Under-Correct | -0.69   | <.001  |
| Delay/Anticipate| 0.70        | <.001   |

Table 2: We report p-values and correlation coefficients for the correlation analysis between each construct and the learned embeddings.
plan to investigate how to account for both the heterogeneity of feedback style and the heterogeneity of task solution preference.

Furthermore, in future work, we plan to conduct another human-subjects study in which we utilize the MIND MELD architecture to train an LfD agent. This LfD agent will be trained on the improved corrective labels provided by MIND MELD and the policy learned by this agent will be compared to the policies learned via DAgger and BC. To do so, we will recruit a set of test participants who will first complete the set of calibration tasks which will be utilized to learn their personalized embeddings. Next, these embeddings will be used to inform the mapping of their feedback when training the learner for the LfD test tasks. Note that we will freeze the parameters $\theta$, $\phi$, and $\phi'$ and we initialize an individual’s personalized embedding to the mean of training participants’ personalized embeddings. The steps comprising our study described in this paper and our future study are shown in Algorithm 1.

In future work, we also plan to apply our approach to a robotic pick-and-place task to determine how MIND MELD’s abilities to differ in a domain with more degrees of freedom.

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