Inferring Personalized Bayesian Embeddings for Learning from Heterogeneous Demonstration

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Abstract

For assistive robots and virtual agents to achieve ubiquity, machines will need to anticipate the needs of their human counterparts. The field of Learning from Demonstration (LfD) has sought to enable machines to infer predictive models of human behavior for autonomous robot control. However, humans exhibit heterogeneity in decision-making, which traditional LfD approaches fail to capture. To overcome this challenge, we propose a Bayesian LfD framework to infer an integrated representation of all human task demonstrators by inferring human-specific embeddings, thereby distilling their unique characteristics. We validate our approach is able to outperform state-of-the-art techniques on both synthetic and real-world data sets.

1 Introduction

Human teams develop shared mental models over years of experience that enable them to anticipate each other's action without explicit communication. This anticipatory ability is key to high-performing teams [Mohammed et al., 2010]. By contrast, it is for the same reason that assistive machines (e.g., "cobots") have not achieved proliferation. Humans currently must explicitly communicate directive to machines, placing a substantial burden on the human teammates. The field of Learning from Demonstration (LfD) has sought to enable robot's to infer such models of human behavior to either imitate the process (e.g., apprenticeship learning [Abbeel and Ng, 2004] or to enable machines to anticipate what actions humans are likely to take so as to take a supportive action [Nikolaidis and Shah, 2012]. LfD has achieved success in learning to drive [Abbeel and Ng, 2004], fly [Coates et al., 2009], and dexterous manipulation [Lee et al., 2015].

However, prior approaches to LfD struggle to handle heterogeneity in human behavior among the demonstrators. The typical approach to LfD is to assume homogeneity, reasoning about the average human, as shown in the left-most diagram of Figure 1. A more recent approach by Nikolaidis et al. performed k-means clustering over the dynamics of the human environment and then learned a separate model of the human for each cluster, as shown in the center diagram of Figure 1 [Nikolaidis et al., 2015]. While a step forward, this approach greatly reduces the total amount of data to train and does not afford leveraging the possible homogeneity that does exist (e.g., adherence to job-specific constraints).

In this paper, we seek to overcome these key gaps in prior work that either ignore or attempt to eliminate heterogeneity. We propose learning personalized Bayesian embeddings, inferred through Bayesian neural network (BNN) backpropagation. These personalized embeddings enables the model to adapt to a person’s unique characteristics while simultaneously leveraging any homogeneity that exists (i.e., uniform adherence to hard constraints). As human demonstration data is often limited in quantity [Amershi et al., 2014], we formulate the learning problem to adopt counterfactual reasoning via pairwise comparisons between the action a human took relative to all actions she did not take in order to provide additional structure for the learning problem and increase the amount of available data.

We evaluate our approach with a synthetic dataset consisting of mock experts’ scheduling heuristics for jobshop scheduling, and a real-world dataset with human gameplay in StarCraft II. We demonstrate the following novel contributions: First, this is the first paper we are aware of to employ BNNs for LfD. Second, we uniquely develop a counterfactual reasoning model with BNNs for imitation learning. Third, we demonstrate new algorithm, which we call the "Hybrid-Bayes Shift" algorithm, to allow for robust performance early on while inferring an accurate Bayesian embedding for long-term, customized behavior prediction. Our results indicate a strong improvement over prior work, e.g., k-means clustering before training.
2 Related Work

Researchers have made significant progress in the field of Learning from Demonstration [Abbeel and Ng, 2004; Konidaris et al., 2011; Odom et al., 2015; Ziebart et al., 2008a; Konidaris et al., 2012; Chernova and Veloso, 2007; Terrell and Mutlu, 2012]. While the ability to capture domain-expert knowledge from demonstration has improved, heterogeneity apparent in the data remains a challenge. Seminal work in LfD by researchers, such as Sammut et al. [2002] found that demonstrator heterogeneity represented a significant challenge to learning from various data sources. In their work, Sammut et al. found that pilots executing the same flight plan created such variance in the data as to make it more practical to learn from a single trajectory and disregard the remaining data. Rather than reduce the utility of our inference model by fitting it to one data point of many, it would be beneficial to reason about the data set and utilize it in its entirety.

To cope with heterogeneity, more recent work by Nikolaidis et al. [2015] performed unsupervised clustering on the data and learned a model for each cluster. The clustering sought to break the dataset into smaller sets that each contain less variance and thus avoided the difficulty faced by Sammut et al. [2002]. There are several caveats of this approach; each model received a much smaller set of data to learn from and thus the model may not have as much representational power as if it were to learn from the entire set. Secondly, given a new data point, this approach required the use of one of the \(k\) models (where \(k\) is the number of clusters) for prediction and did not fully account for cases where the human demonstrator is a combination of the clusters. Lastly, this approach did not account for variability within a cluster. Personalizing a model to adhere to a specific person rather than utilizing a group model can result in large performance gains. We note that the closest work to ours is by Killian et al. [2017]. However, these researchers consider only a synthetic dataset and only model transition dynamics rather than decision-making behavior à la LfD.

3 Preliminaries

LfD mechanisms are typically based upon a Markov Decision Process (MDP). Formally, a MDP is a 5-tuple \(M = (S, A, T, \gamma, R)\) where \(S\) is a set of states, \(A\) is a set of actions, \(T: S \times A \times S \to [0,1]\) is a transition function, where \(T(s, a, s')\) is the probability of being in state \(s'\) after executing action \(a\) in state \(s\), \(R: S \to \mathbb{R}\) (or \(R: S \times A \to \mathbb{R}\)) is a reward function that takes the form of \(R(s)\) or \(R(s, a)\) depending upon whether the reward is assessed for being in a state or for taking a particular action within a state, and \(\gamma \in [0,1]\) is the discount factor for future rewards. The goal is then to learn a policy, \(\pi: S \to A\) to maximize the policy’s future expected reward, \(V^\pi(s) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t | s_0 = s]\), where the policy begins in state \(s_0 = s\) and follows policy \(\pi\) thereafter, receiving reward, \(r_t\), at each time step.

The problem of LfD is to receive 1) a set of trajectories provided by a human demonstrator, \(\{(s_t, a_t), t \in \{1,2,...\}\}\) and 2) an MDP sans reward function, \(R\), and recover a policy that can predict the correct state-action sequence a human would take in a novel situation which would maximize the human’s latent reward function. There are two basic approaches: goal-based reasoning and policy-based reasoning. Goal-based reasoning captures the work of the Inverse Reinforcement Learning Community [Abbeel and Ng, 2004], in which one attempts to infer the latent reward function (i.e., a set of weights over hand-specified feature counts) and then construct a policy to maximize this reward function. On the other hand, policy-based reasoning seeks to directly learn a mapping from states to actions [Chernova and Veloso, 2007]. Goal-based reasoning approaches typically require one to assume a reward basis function (e.g., a weighted, linear combination of feature counts) [Abbeel and Ng, 2004] or a Bayesian prior over hand-specified goals [Ziebart et al., 2008b]. In this work, we desire to have a model that does not require one to have access to such information; as such, we develop a policy learning-based approach.

4 BNNs for Human Control Policy Modeling

In this section, we present our model for inferring personalized embeddings to capture the the homo- and heterogeneity among human demonstrators in LfD tasks. This formulation is the first we know of for explicitly reasoning about heterogeneity with a single, integrated model in LfD.

![Figure 2: Bayesian Neural Network Diagram.](image-url)
action, and subscript $j$ corresponds to the probability for action $j \in \{1, 2, \ldots, |A|\}$. \( \alpha \subset (-\infty, +\infty) \) corresponds to a hyperparameter that can be tuned in order to learn a closer approximate distribution to \( y_{t}^i \).

\[
D_{\alpha}(\hat{y}_{t}^i \| \hat{c}_{y_{t}^i}) = \frac{1}{\alpha - 1} \log \left( \sum_{j=t}^{\alpha} \left( \frac{\hat{y}_{t,j}^i}{\hat{c}_{y_{t,j}^i}} \right)^{\alpha - 1} \right)
\]  

(1)

This loss is then backpropagated through the network to update model parameters \( \theta \) and the personalized embedding \( \omega \) via stochastic gradient descent as shown in Equations 2 and 3, respectively, at iteration \( i \).

\[
\theta(t+1) \leftarrow \theta(t) + \alpha \frac{\partial D_{\alpha}(\hat{y}_{t}^i \| \hat{c}_{y_{t}^i})}{\partial \theta}
\]

(2)

\[
\omega(t+1) \leftarrow \omega(t) + \alpha \frac{\partial D_{\alpha}(\hat{y}_{t}^i \| \hat{c}_{y_{t}^i})}{\partial \omega}
\]

(3)

When applying the algorithm during runtime (i.e., testing) for a new human demonstrator, \( p' \), one updates the embedding, \( \omega' \), via Equation 3; however, the network’s parameters, \( \theta \), remain static. This hybrid approach enables one to balance the bias-variance tradeoff, grounding the model in parameters common to all demonstrators via \( \theta \) while tailoring a subset of the parameters, \( \omega \), to tune the model for an individual.

We note that there are two common approaches to training. One approach is to establish well-tuned learning rates via manual tuning or direct optimization [Hsieh and Shanechi, 2016] with the important distinction that we include \( \omega \) in \( \theta \) and used to predict which action the expert would ultimately take at each moment in time. Gombolay et al. [2016] have applied counterfactual reasoning in BNNs. This paper is the first to our knowledge that comparing pairs of actions can outperform a multi-class classification model. This paper is the first to our knowledge that has applied counterfactual reasoning in BNNs.

Our pairwise approach is similar to that of Gombolay et al. [2016] with the important distinction that we include Bayesian reasoning. For each observation, we receive a set of features for each action, \( x_{a,t} \), as well as a set of state features, \( \bar{x}^t \). For an observation in which action \( a \in A \) was selected, we construct training example-label pairs \( \langle x_{a,t}^t, y_{a,t}^t \rangle \) according to Equations 4-7.

\[
x_{a,t}^t = [\omega, \bar{x}^t, x_{a}^t - x_{a}^{t-1}]
\]

(4)

\[
y_{a,t}^t = 1
\]

(5)

\[
x_{a,t}^t = [\omega, \bar{x}^t, x_{a}^t - x_{a}^{t-1}]
\]

(6)

\[
y_{a,t}^t = 0
\]

(7)

We generate these examples for all \( a' \in A \setminus a \) and for all time observation time steps. After training a classifier, \( f \), on this data set, we can predict the action selected by the user as shown in Equation 8.

\[
\hat{a} = \arg \max_{a \in A} \sum_{a' \subset A} f(a, a', \omega)
\]

(8)

5.1 Bayesian Action Embeddings for Counterfactual Reasoning

While the aforementioned approach to counterfactual reasoning is novel in application to BNNs for LfD, we develop an additional contribution demonstrating the capability of BNNs. One of the challenges with the approach in Equations 4-7 is that one must have access to action-specific features. In the context of our synthetic scheduling environment, the action features are readily available in the form of information about which agent is performing which task and the features of that task (e.g., its location, deadline, duration, etc.). However, in our evaluation with real-world data from StarCraft II, such features are not directly provided.

In our evaluation of counterfactual reasoning in StarCraft II, we leverage BNNs to infer action embeddings by training a state transition model, \( f \) to take as input a state, \( s_t \) and an action embedding \( \omega_a \), and predict the next state in a game’s replay, \( s_{t+1} \). By minimizing the Rényi divergence (Equation 1 between \( s_{t+1} \) and \( f(s_t, \omega_a) \), for each action across all time steps and games, we can infer a player-invariant, action embedding, \( \omega_a \), that can serve in lieu of \( x_a^t \) in Equation 4 and 6.

5.2 Robust Bayesian Prediction

One of the challenges with BNN-based prediction is that the model can provide highly-erroneous predictions at the beginning of a testing episode, when the Bayesian embedding has not yet converged from feedback. In the short-term, a baseline neural network can outperform a BNN. Yet, in the long-term, as we will see in our results section, a BNN will ultimately overtake the performance of baseline methods as the embedding converges and the BNN hones in on the desired, customized prediction model. To achieve the best of both worlds, we develop a hybrid methodology we denote Hybrid-Bayes Shift.

We provide a pseudo-code description in Algorithm 1. We experimented with a number of criteria (e.g., determining whether the BNN method has a higher prediction accuracy over the previous \( k \) time steps relative to the baseline method) but found that the best performance is achieved when the switch, between making predictions using the baseline method and the BNN, occurs after the embedding has converged, as described by Line 7 of Algorithm 1.

6 Data Sets

Two different data sets were used to validate our methodology, a synthetic scheduling environment and a real-world dataset of gameplay from StarCraft II.
Algorithm 1 Hybrid-Bayes Shift

1: Input: $\pi_{\theta, \omega}^{NN}$, $\pi_{\phi}^{NN}$
2: $t \leftarrow 0$
3: $\pi \leftarrow \pi_{\phi}^{NN}$
4: while episode not finished do
5: $\hat{y}_t \leftarrow \pi(x_t)$
6: $\omega^{(t+1)} \leftarrow \text{Apply Equation 3}$
7: if $||\omega^{(t-1)} - \omega(t)|| < \epsilon$ then
8: $\pi \leftarrow \pi_{\theta, \omega}^{NN}$
9: end if
10: $t \leftarrow t + 1$
11: end while

6.1 Scheduling Environment

The first environment we use to explore BNNs for LfD is a synthetic environment that we can control, probe, and intuit to empirically validate the efficacy of our proposed method. The environment we develop is similar to one by [Gombolay et al., 2016] developed for selecting scheduling actions (i.e., which agent to assign to which task) for a jobshop scheduling problem. The prior version of this benchmark employed one of three heuristic policies for selecting actions based upon the characteristics of the scheduling instance. These characteristics were made available to the observing LfD algorithm as to make the policy inference problem fully observable.

We adapt this environment by no longer providing our LfD algorithms the features necessary to tease out which heuristic would be applied for a given problem instance. Instead, the behavior appears heterogeneous and without clear rationale. For an LfD algorithm to properly handle this obfuscation, the algorithm must infer which policy is being employed based upon feedback from the actions being selected in real-time. We note that the dataset is not exclusively heterogeneous – each policy adheres to basic scheduling constraints (e.g., no two agents can occupy the same physical location, etc.). As such, we expect even algorithms that assume homogeneity may have some success in cases in which only one or a few actions satisfy all scheduling constraints.

6.2 StarCraft II

A real-world data set with gameplay from StarCraft II is used to evaluate the utility of a personalized Bayesian embedding generated from a BNN. This data was provided alongside the StarCraft II API PySC2 [Vinyals et al., 2017]. This dataset contains a large number of 1-vs.-1 replays that affords access to game state-action information at every frame, information regarding the outcome of the game, and the ranking of the players. Each game can be thought as a demonstration trajectory by a human-human dyad.

The state of the game at any time step within the trajectory consists of several images pertaining to where units and buildings are located alongside information about visibility regions, and vectorized state information pertaining to the amount of resources, buildings, and units in the game. The action taken in every frame can be one of hundreds, and thus as a simplification, we have produced forty actions that are representative of all.

7 Results and Discussion

We assess the utility of inferring personalized Bayesian embeddings for LfD using the synthetic scheduling environment and StarCraft II replays described in Section 6.

7.1 Synthetic Scheduling Environment

We consider scheduling demonstrations in which a mock expert chose one of three heuristic policies to assign twenty tasks to two agents and sequence those tasks through time. Several LfD architectures were compared to test their ability on a heterogeneous demonstration set and to further display the utility of applying a BNN to LfD. We compared a:

- neural network à la Sammut et al. [2002])
- set of k neural networks, each trained upon data clustered through k-means à la Nikolaidis et al. [2015]
- a neural network where the data was first segmented using a Gaussian Mixture Model (GMM), and then input into a network augmented with its probability of coming from each segment
- Bayesian Neural Network
- Long-Short-Term-Memory (LSTM) network that can serve to learn temporal elements of the data
- Bayesian LSTM (B-LSTM), which is an LSTM with a Bayesian embedding in the input layer

Sample models of the networks and details regarding constraint satisfaction and data generation can be found on https://github.com/ghost12331/HLfD. Each of the methods described above were trained given 3, 9, 15, 150, and 1500 schedules of training data.

Standard Approach

The performance of each network architecture is shown in Figure 3, where the network is trained to take features of the state of the scheduling environment, including features describing each and every scheduling action, and map it to the action the mock expert would have selected. This figure demonstrates that our Hybrid-Bayes Shift method (blue line in Figure 3) is able to outperform all baselines when the amount of data available for training is greater than three instances by explicitly reasoning about embedding convergence.

Bayesian Counterfactual Reasoning

Next, we consider Bayesian counterfactual reasoning to increase the amount of information apparent in a given set, provide additional structure to the learning problem, and infer an embedding to represent the heterogeneity apparent in a given individual.

A slight difference between the procedure of using Bayesian counterfactual reasoning in the synthetic scheduling environment and StarCraft II is how the action specific features are obtained. In the scheduling environment, these features could be obtained directly from the data; however, in StarCraft, they could not. Our approach to learn these embeddings is to utilize an action-BNN, where the latent embedding is a vector of action specific features. We learn the model $\pi_{\theta} : S_t \times \Omega_A \rightarrow S_{t+1}$, where $S_t$ is representative of the game state at time $t$, $S_{t+1}$ is the game state at time $t + 1$, and
Ω_A refers to a set of action-specific embeddings. After this model is learned, this set can be extracted and pairwise comparisons can be conducted between the set of actions taken, and not taken, as in Equations 4 - 7 with the exception that multiple actions may be taken.

Figure 4 provides evidence that counterfactual reasoning greatly improves the power of our LfD models relative to the results from Figure 3. Utilizing counterfactual reasoning with Bayesian inferences allows for an approximately a 4-fold increase in the capability of the BNN to predict the task to schedule. As the BNN is again able to outperform conventional approaches in LfD, this provides further verification that inferring personalized Bayesian embeddings can aid in anticipatory models. With counterfactual reasoning, we can see that the BNN and the BNN-based Hybrid-Bayes Shift method achieve approximately the same performance and outperform the method of [Nikolaidis et al., 2015]. We can also see that the top-3 prediction accuracy for our method approaches 80% and is strikingly robust to the amount of training data available, only varying from 75% for three scheduling instances to a peak of 80% for 150 available demonstrations.

7.2 Real World Gameplay Data from StarCraft II

Having shown promising results for the use of Bayesian-based neural networks, the Hybrid-Bayes Shift method, and counterfactual reasoning, we seek to replicate our findings in a more complex domain with real-world data: StarCraft II. Specifically, we learn the gameplay policy of a given player playing StarCraft II. We again utilize the standard and counterfactual approach, and note the differences between the two methods. As our metric, we compare the performance of the ability to model a player policy by looking at the % difference in loss in comparison with a baseline neural network. Further information about the architecture or hyperparameters used can be found on https://github.com/ghost12331/HLfD.

Figure 3: This figure depicts the prediction accuracy for the scheduling environment training to select the correct action.

Figure 4: This figure depicts the top-1 prediction accuracy with counterfactual reasoning for the scheduling environment.

Figure 5: This figure depicts the top-3 prediction accuracy with counterfactual reasoning for the scheduling environment.

Standard Approach

The performance of each method, BNN, B-LSTM, LSTM, and a baseline NN is shown in figure. We do not include the GMM and k-means-based methods of [Nikolaidis et al., 2015] as these were shown to underperform relative to our Bayesian approaches to LfD. For this policy learning problem, each model is given the current game-state and attempts to predict the action that will be taken at that timestep.

In Figure 6, we report the results of a BNN, LSTM, and B-LSTM trained using the standard, multi-class classification (i.e., not counterfactual) approach. We can see that the LSTM outperformed the baseline, NN, model by approximately 1%, which is to be expected given an LSTM’s ability to learn a dynamic embedding passed from state to state. Interestingly, we found that a BNN – without any recurrent structure except for its backpropagated embedding – outperformed an LSTM model achieving an almost 10% advantage over the baseline. We also found evidence that the B-LSTM performed as well
as the BNN but with additional gains in early gameplay (i.e., the first 20% of the game). These results provide strong evidence that the embedding learned for an individual player captures impactful information not easily recovered with a mere application of an LSTM.

Bayesian Counterfactual Reasoning
We report the performance of our action-embedding-learning method for counterfactual reasoning in BNNs in Figure 6. We can see that the BNN model trained via counterfactual reasoning (green curve in Figure 6) using Bayesian action embeddings achieves a factor of 3 reduction in the loss relative to a neural network baseline for the majority of the games’ durations. These promising results show the potential of BNNs for adaptive learning from heterogeneous demonstration, BNNs for learning action embeddings in such domains, and BNNs for counterfactual reasoning.

7.3 Discussion
In our empirical evaluation, we provide evidence of the utility of learning personalized Bayesian embeddings for LfD tasks in two domains: one synthetic environment for jobshop scheduling and a virtual domain with real human gameplay data. Further, we show that counterfactual reasoning can provide a multi-fold improvement in performance. Finally, we demonstrate a simple, but powerful algorithm (Algorithm 1) can compensate for the inaccuracy of a BNN’s prediction before the embedding has converged. In the field of LfD, our approach achieves superior performance relative to state-of-the-art techniques [Nikolaidis et al., 2015].

8 Limitations & Future Work
We also wanted to determine whether BNNs emergently produced embeddings that were person-specific but network-invariant. In other words, we ask whether a Bayesian embedding learned from one network can be fed into a different network – perhaps one that was not able to leverage feedback to infer its own embedding online. Such a situation might arise from attempting to infer a player-specific value function over the course of a single game without knowing that game’s outcome. One could train two networks, an action-prediction network and a value-prediction network. The action-prediction network could benefit from dense feedback (i.e., observing which action a player took at each time step) to infer an accurate embedding. The value-prediction network could likewise be trained on a point estimate of the expected reward, $V^\pi_\theta,\omega(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t | s_t = s \right]$, when following a player-specific policy $\pi_\theta,\omega$ parameterized by network parameters $\theta$ and personalized embedding $\omega$. However, when attempting to predict the value of a new player in state $s$ during a real game (i.e., a “cost-to-go” given a spare reward structure assessed at the end of the game), one would not have the benefit of such feedback to be able to infer a Bayesian embedding. As such, one might seek to determine whether an embedding could be inferred via the action-network and passed to the value network.

We conducted an experiment to investigate this possibility by employing a dense-feedback network to infer an embedding for a sparse-feedback network in the domain of StarCraft II. As shown in Figure 7, our initial investigation did not yield positive results. This figure provides evidence that the B-LSTM value network actually performed worse than a non-Bayesian LSTM. We hypothesize that the LSTM is having to adapt its recurrent embedding to override the changing Bayesian input provided from the action network, which was a BNN. These results are disappointing, suggesting that such an emergence of network-invariant, personalized embeddings is not guaranteed to happen. This result is, perhaps, unsurprising as the embedding is not being tailored to directly reduce the loss of the value network. In future work, we will explore the theoretical and algorithmic conditions for which such an emergence could happen. For example, one approach may be to adopt a meta-learning approach in which one seeks to repeatedly learn a Bayesian embedding for a person such that the distance between the converged embeddings, and
across networks, at the end of an episode is minimized and the distance between the embeddings at the beginning of the episode is maximized. Such an approach could compel the networks to learn an intrinsic mechanism to relate persons in the way that generative adversarial networks provide evidence of embeddings amenable to vector addition and subtraction [Radford et al., 2015].

9 Conclusion

In this paper, we investigated a novel formalism for learning from heterogeneous demonstration via BNNs. We showed that BNNs can be leveraged to infer personalized, latent embeddings to enable the network to better adapt to the unique characteristics of an individual’s decision-making behavior. We also developed a Bayesian counterfactual approach that greatly increases the power of these networks for small data set with well-defined action descriptors. Finally, we proposed future work in learning personalized, network-independent embeddings to facilitate cross-network embedding sharing. Our results on synthetic and real-world data sets show a strong improvement over state-of-the-art baselines for learning from heterogeneous demonstration.

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