EXPLAINING BY IMITATING: UNDERSTANDING DECISIONS BY INTERPRETABLE POLICY LEARNING

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ABSTRACT

Understanding human behavior from observed data is critical for transparency and accountability in decision-making. Consider real-world settings such as healthcare, where modeling a decision-maker's policy is challenging—with no access to underlying states, no knowledge of environment dynamics, and no allowance for live experimentation. We desire learning a data-driven parameterization of decision behavior that (1) inheres *transparency by design*, (2) accommodates *partial observability*, and (3) operates *completely offline*. To satisfy these key criteria, we propose a novel model-based Bayesian method for *interpretable policy learning* ("INTERPOLE") that jointly estimates the (possibly biased) belief-update process of decision-makers together with their (possibly suboptimal) policies. Through experiments on both simulated and real-world data for the problem of Alzheimer's disease diagnosis, we illustrate the potential of our method as an investigative device for understanding human decision-making behavior.

1 INTRODUCTION

A principle challenge in modeling human behavior is in obtaining a transparent *understanding* of decision-making processes. In medical diagnosis, for instance, there is often significant regional and institutional variation in clinical practice [1], much of it the leading cause of rising healthcare costs [2]. The ability to quantify different decision-making processes is the first step towards a more systematic understanding of medical practice. Purely by observing demonstrated behavior, our principal objective is to answer the question: Under any given state of affairs, what actions are (more/less) likely to be taken, and why?

We address this challenge with our eyes on three key criteria. First, we desire a method that is *transparent by design*. Specifically, a transparent description of behavior should locate the factors that contribute to individual decisions, in a language readily understood by domain experts [3, 4]. This will be clearer per our subsequent formalism, but we can already note some contrasts: Classical imitation learning—popularly by reduction to supervised classification—does not fit the bill, since the black-box hidden states of RNNs are rarely amenable to meaningful interpretation. Similarly, apprentice learning algorithms—popularly through inverse reinforcement learning—do not meet the bar either, since the high-level nature of reward mappings is not informative as to each individual action observed in the data. Rather than focusing purely on *replicating* actions (imitation learning) or on *matching* expert performance (apprenticeship learning), our chief pursuit lies in *understanding* demonstrated behavior.

Second, real-world environments such as healthcare are often *partially observable* in nature. This requires modeling the accumulation of information from entire sequences of past observations—an endeavor that is prima facie at odds with the goal of transparency. For instance, in a fully-observable setting, (model-free) behavioral cloning is arguably transparent in providing simple mappings of states to actions; however, coping with partial observability using any form of recurrent function approximation immediately lands in black-box territory. Similarly, while (model-based) techniques have been developed for robotic control, their transparency hinges on fully-observable kinematics.

Finally, in realistic settings it is often impossible to experiment freely—especially in high-stakes environments with real products and patients. The vast majority of recent work in (inverse) reinforcement learning has focused on games, simulations, and gym environments where access to live interaction is unrestricted. By contrast, in healthcare the environment dynamics are neither known a priori,

Table 1: *Comparison with Related Work.* INTERPOLE satisfies our key criteria of (1) transparency by design, (2) partial observability, and (3) offline learning, and makes no assumptions regarding unbiasedness of beliefs nor optimality of policies. In each diagram, z, b, q_*, a, and π respectively denote observations, beliefs, (optimal) q-values, actions, and policies; **bold** denotes learned quantities, *italics* denote quantities that are known (or can be queried), and "†" denotes jointly-learned quantities.

Approach		Prototype	Overview	(1)	(2)	(3)	Beliefs	Policy
Imitation Learning	BC	[5]	$z \xrightarrow[\text{(supervised learning)}]{\boldsymbol{\pi(a\|z)}} a$	✗	✗	✓	(N/A)	No assumption
	GAIL	[6]	$z \xrightarrow[\text{(informed by } \textit{dynamics})]{\boldsymbol{\pi(a\|z)}} a$	✗	✗	✗	(N/A)	No assumption
	MB-IL	[7]	$z \xrightarrow[\text{(informed by } \textbf{environment model})]{\boldsymbol{\pi(a\|z)}} a$	✓	✗	✓	(N/A)	No assumption
Apprenticeship Learning	IRL	[8]	$z \xrightarrow[\text{(reinforcement learning)}]{\textbf{rewards}, \textit{dynamics}} q_* \xrightarrow[\text{(argmax)}]{} a$	✗	✗	✗	(N/A)	Optimal
	PO-IRL	[9]	$z \xrightarrow[\text{(inference)}]{\textit{dynamics}} b \xrightarrow[\text{(reinforcement learning)}]{\textbf{rewards}, \textit{dynamics}} q_* \xrightarrow[\text{(argmax)}]{} a$	✗	✓	✗	Unbiased	Optimal
	Off. PO-IRL	[10]	$z \xrightarrow[\text{(inference)}]{\textbf{dynamics}^\dagger} b \xrightarrow[\text{(reinforcement learning)}]{\textbf{rewards}^\dagger\ \textbf{dynamics}^\dagger} q_* \xrightarrow[\text{(argmax)}]{} a$	✗	✓	✓	Unbiased	Optimal
INTERPOLE		**(Ours)**	$z \xrightarrow[\text{(inference)}]{\textbf{decision dynamics}^\dagger} b \xrightarrow{\boldsymbol{\pi(a\|b)} \sim \textbf{decision boundaries}^\dagger} a$	✓	✓	✓	No assumption	No assumption

nor estimable by repeated exploration. We want a data-driven parameterization of behavior that is learnable in a *completely offline* fashion, yet does not rely on knowing/modeling any true dynamics.

Contributions. Our contributions are three-fold. First, we propose a model for interpretable policy learning ("INTERPOLE"), where sequential observations are aggregated via an agent's *decision dynamics* (i.e. subjective belief-update process), and sequential actions are determined via the agent's *decision boundaries* (i.e. probabilistic belief-action mapping). Second, we suggest a Bayesian learning algorithm for estimating the model, simultaneously satisfying the key criteria of transparency, partial observability, and offline learning. Third, through experiments on both simulated and real-world data for the problem of Alzheimer's disease diagnosis, we illustrate the potential of our method as an investigative device for understanding human decision-making behavior.

2 RELATED WORK

The goal of our work is to seek an *interpretable* parameterization of observed behavior to understand the actions taken by an agent. Fundamentally, this is in contrast to methods in *imitation* learning (which seek to best replicate the demonstrated policies), as well as to techniques in *apprenticeship* learning (which seek to match some notion of performance).

Imitation Learning. In fully-observable settings, behavior cloning (BC) readily reduces the imitation problem to one of supervised classification [11, 12, 5]; i.e. actions are simply regressed on observations. While this can be extended to account for partial observability by parameterizing policies via recurrent function approximation [13], it immediately gives up on ease of interpretability per the black-box nature of RNN hidden states. A variety of adversarial techniques based on state-distribution matching—most famously, generative adversarial imitation learning (GAIL)—have recently been developed, which account for information in the rollout dynamics of the environment during policy learning [14, 6]. However, such methods require repeated online rollouts of intermediate policies during training, and also face the same black-box problem as BC in partially observable settings. Clearly in model-free imitation, it is difficult to admit both transparency and partial observability.

Specifically with an eye on explainability, Info-GAIL [15] proposes an orthogonal notion of "interpretability" that hinges on finding clusters of similar demonstrations to explain variations in behavior. However, as with GAIL it suffers from the need for live interaction for learning. Finally, several model-based techniques for imitation learning (MB-IL) have been studied in the domain of robotics. [16] consider kinematic models designed for robot dynamics, while [17] and [7] consider (non-linear) autoregressive exogenous models. However, such approaches operate within fully-observable settings, and are restricted to models tailored to specific robotic applications under consideration.

Apprenticeship Learning. In subtle distinction to imitation learning, methods in apprenticeship learning first assume that observed behavior is optimal with respect to some underlying reward function. Apprenticeship thus proceeds indirectly—first via inverse reinforcement learning (IRL) to infer a reward function, which subsequently (after appropriate optimization) generates behavior that matches the performance of the original as gauged by rewards [18, 19, 20, 8]. These approaches have been extended [21, 9] to cope with partial observability (PO-IRL), and to offline settings via off-policy evaluation [22, 23, 24] or learned environment models [10].

However, a shortcoming of such methods is the requirement that the demonstrated policy in fact be *optimal* with respect to a true reward function that lies within an (often limited) hypothesis class under consideration. Further, learning the true environment dynamics corresponds to the requirement that policies be restricted to the class of functions that map from *unbiased* beliefs (cf. exact inference) into actions. Perhaps most importantly, due to the indirect, task-level nature of reward functions, inverse reinforcement learning is essentially opposed to our central goal of transparency—that is, in providing direct, action-level descriptions of behavior.

Towards INTERPOLE. In contrast, we avoid making any assumptions as to either the unbiasedness of beliefs or optimality of policies. After all, the former requires estimating (externally) "true" environment dynamics, and the latter requires specifying (objectively) "true" classes of reward functions—neither of which are necessary with respect to our goal of transparently describing individual actions. Instead, INTERPOLE simply seeks the *most plausible explanation* in terms of (internal) decision dynamics and (subjective) decision boundaries. To the best of our knowledge, our work is the first to tackle all three of our key criteria—while making no assumptions on the generative process behind behaviors. Table 1 contextualizes our work, showing prototypical incarnations of related approaches and their graphical models.

3 INTERPRETABLE POLICY LEARNING

We start by formalizing the INTERPOLE model of behavior, introducing notions of decision dynamics and decision boundaries. In the next section, we then suggest a Bayesian learning algorithm for estimating the model's parameters from observed data.

Problem Setup. Consider a partially-observable decision-making environment in discrete time. At each time step t, the agent takes some action $a_t \in A$ and observes some outcome $z_t \in Z$.[1] We have at our disposal an observational dataset of *demonstrations* $\mathcal{D} = \{(a_1^i, z_1^i, \ldots, a_{\tau_i}^i, z_{\tau_i}^i)\}_{i=1}^n$ by an agent, where τ_i is the length of the i-th trajectory. In the sequel, we shall omit indices i unless explicitly required. Denote with $h_t \doteq (a_1, z_1, \ldots, a_{t-1}, z_{t-1})$ the observed history at the beginning of step t, where $h_1 \doteq \emptyset$. Analogously, let $H_t \doteq (A \times Z)^{t-1}$ give the set of all possible histories at the start of step t, where $H_1 \doteq \{\emptyset\}$, and let $H \doteq \cup_{t=1}^{\infty} H_t$.

A proper policy π is a map $\pi \in \Delta(A)^H$ from observed histories to action distributions, where $\pi(a|h)$ is the probability of taking action a given h. We assume that $\mathcal{D}$ is generated by an agent acting according to some *behavioral policy* π_{b}. The problem we tackle, then, is precisely how to obtain an interpretable parameterization of π_{b}. We proceed in two steps: First, we describe a parsimonious belief-update process for accumulating histories—which we term *decision dynamics*. Then, we take beliefs to actions through a probabilistic mapping—which gives rise to *decision boundaries*.

Decision Dynamics. We model belief-updates by way of an input-output hidden Markov model (IOHMM) identified by the tuple (S, A, Z, T, O, b_1). Here, S denotes the finite set of underlying states, $T \in \Delta(S)^{S \times A}$ denotes the transition function such that $T(s_{t+1}|s_t, a_t)$ gives the probability of transitioning into state s_{t+1} after taking action a_t in state s_t, and $O \in \Delta(Z)^{A \times S}$ denotes the observation function such that $O(z_t|a_t, s_{t+1})$ gives the probability of observing z_t after taking action a_t and transitioning into state s_{t+1}. Finally, let beliefs $b_t \in \Delta(S)$ indicate the probability $b_t(s)$ that the environment exists in any state $s \in S$ at time t, and let b_1 give the initial state distribution.

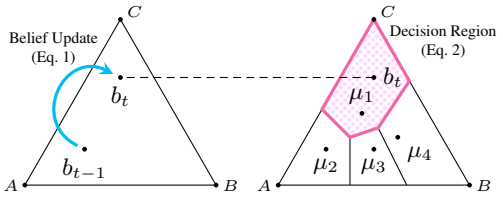
In order to aggregate observed histories in the form of beliefs, we identify $b_t(s)$ with $\mathbb{P}(s_t = s|h_t)$—an interpretation that leads to the (familiar) recursive belief-update process:

$$b_{t+1}(s') \propto \textstyle\sum_{s \in S} b_t(s) T(s'|s, a_t) O(z_t|a_t, s') \tag{1}$$

[1] While we take it here that Z is finite, our method can easily be generalized to allow continuous observations.

where in our problem setting, quantities S, A, Z are known, and T, O, b_1 are unknown. A key distinction bears emphasis: We do not require that this latter set of quantities correspond to (external) environment dynamics—and we do not obligate ourselves to recover any such notion of "true" parameters. To do so would imply the assumption that the agent in fact performs exactly *unbiased* inference on a perfectly known model of the environment, which is restrictive. It is also unnecessary, since our mandate is simply to model the (internal) mechanics of decision-making—which could well be generated from *possibly biased* beliefs or imperfectly known models of the environment. In other words, our objective (see Equation 3) of simultaneously determining the most likely beliefs (cf. decision dynamics) and policies (cf. decision boundaries) is fundamentally more parsimonious.

Decision Boundaries. Given decision dynamics, a policy is then equivalently a map $\pi \in \Delta(A)^{\Delta(S)}$. Now, what is an interpretable parameterization? Consider the three-state example in Figure 1. We argue that a probabilistic parameterization that directly induces "decision regions" (cf. panel 1b) over the belief simplex is uniquely interpretable. For instance, strong beliefs that a patient has underlying mild cognitive impairment may map to the region where a specific follow-up test is promptly prescribed; this parameterization allows clearly locating such regions—and their boundaries.



(a) **Decision Dynamics** (b) **Decision Boundaries**

Figure 1: *The* INTERPOLE *Model.* $S = \{A, B, C\}$ and $A = \{1, 2, 3, 4\}$. (a) Beliefs are updated per Equation 1. (b) Actions are chosen w.r.t. relative locations of mean vectors (Equation 2).

Precisely, we parameterize policies in terms of $|A|$-many "mean" vectors that correspond to actions:

$$\pi(a|b) = e^{-\eta\|b-\mu_a\|^2} / \textstyle\sum_{a' \in A} e^{-\eta\|b-\mu_{a'}\|^2}, \quad \textstyle\sum_{s \in S} \mu_a(s) = 1 \tag{2}$$

where $\eta \geq 0$ is the inverse temperature, $\|\cdot\|$ the ℓ_2-norm, and $\mu_a \in \mathbb{R}^{|S|}$ the mean vector corresponding to action $a \in A$. Intuitively, mean vectors induce decision boundaries (and decision regions) over the belief space $\Delta(S)$: At any time, the action whose corresponding mean is closest to the current belief is most likely to be chosen. In particular, lines that are equidistant to the means of any pair of actions form decision boundaries between them. The inverse temperature controls the transitions between such boundaries: A larger η captures more deterministic behavior (i.e. "abrupt" transitions), while a smaller η captures more stochastic behavior (i.e. "smooth" transitions). Note that $\eta = 0$ recovers uniformly random policies, and $\eta \to \infty$ recovers argmax policies.

A second distinction is due: The exponentiated form of Equation 2 should not be confused with typical Boltzmann [19] or MaxEnt [25] policies common in RL: These are indirect parameterizations via optimal/soft q-values, which themselves require approximate solutions to optimization problems; as we shall see in our experiments, the quality of learned policies suffers as a result. Further, using q-values would imply the assumption that the agent in fact behaves *optimally* w.r.t. an (objectively) "true" class of reward functions (e.g. linear), which is restrictive. It is also unnecessary, as our mandate is simply to capture their (subjective) tendencies toward different actions—which are generated from *possibly suboptimal* policies. In contrast, by directly partitioning the belief simplex into probabilistic "decision regions", INTERPOLE's mean-vector parameterization is immediately interpretable.

Learning Objective. In a nutshell, our objective is to identify the most likely parameterizations T, O, b_1 for decision dynamics and η, $\{\mu_a\}_{a \in A}$ for decision boundaries given observed data:

$$\begin{aligned} &\text{Given: } \mathcal{D}, S, A, Z \\ &\text{Determine: } T, O, b_1, \eta, \{\mu_a\}_{a \in A} \end{aligned} \tag{3}$$

In the next section, we propose a Bayesian algorithm for INTERPOLE that finds the maximum a posteriori (MAP) estimate of these quantities.

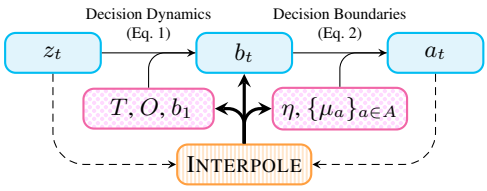


Figure 2: *The* INTERPOLE *Objective*. Inputs (observed data) are fed in through dashed lines. Outputs (estimates) are issued in bold.

4 BAYESIAN INTERPRETABLE POLICY LEARNING

Denote with $\theta \doteq (T, O, b_1, \eta, \{\mu_a\}_{a \in A})$ the set of parameters to be determined, and let θ be drawn from some prior $\mathbb{P}(\theta)$. In addition, denote with $\tilde{\mathcal{D}} = \{(s_1^i, \ldots, s_{\tau_i+1}^i)\}_{i=1}^n$ the set of underlying

(unobserved) state trajectories, such that $\mathcal{D} \cup \bar{\mathcal{D}}$ gives the *complete* (fully-observed) dataset. Then, the complete likelihood—of the unknown parameters θ given $\mathcal{D} \cup \bar{\mathcal{D}}$ is per the following:

$$\mathbb{P}(\mathcal{D}, \bar{\mathcal{D}}|\theta) = \underbrace{\prod^{n}\prod^{\tau} \pi(a_t|b_t[T, O, b_1, h_{t-1}])}_{\text{action likelihoods}} \times \underbrace{\prod^{n} b_1(s_1) \prod^{\tau} T(s_{t+1}|s_t, a_t) O(z_t|a_t, s_{t+1})}_{\text{observation likelihoods}} \quad (4)$$

where $\pi(\cdot|\cdot)$ is described by parameters η and $\{\mu_a\}_{a\in A}$, while $b_t[\cdot]$ is a function of T, O, b_1, and h_{t-1} defined recursively as given in Equation 1. Since we do not have access to $\bar{\mathcal{D}}$, we employ an expectation-maximization (EM)-like algorithm to maximize the posterior probability $\mathbb{P}(\theta|\mathcal{D}) = \mathbb{P}(\mathcal{D}|\theta)\mathbb{P}(\theta)/\int \mathbb{P}(\mathcal{D}|\theta)\mathrm{d}\mathbb{P}(\theta)$ over the parameters.

Bayesian Learning. Given an initial estimate $\hat{\theta}^0$ of the unknown parameters, we iteratively improve the estimate by performing the following two steps at each iteration k:

- *"E-step":* Compute the expected log-likelihood of parameters θ given the previous estimate $\hat{\theta}^{k-1}$:

$$Q(\theta; \hat{\theta}^{k-1}) \doteq \mathbb{E}_{\bar{\mathcal{D}}|\mathcal{D},\hat{\theta}^{k-1}}[\log \mathbb{P}(\mathcal{D}, \bar{\mathcal{D}}|\theta)] = \textstyle\sum_{\bar{\mathcal{D}}} \log \mathbb{P}(\mathcal{D}, \bar{\mathcal{D}}|\theta)\mathbb{P}(\bar{\mathcal{D}}|\mathcal{D}, \hat{\theta}^{k-1}) \quad (5)$$

  where we compute the necessary marginalizations of the joint distribution $\mathbb{P}(\bar{\mathcal{D}}|\mathcal{D}, \hat{\theta}^{k-1})$ by way of a forward-backward procedure (detailed procedure in Appendix A.1).

- *"M-step":* Compute a new estimate $\hat{\theta}^k$ that improves the expected log-posterior—i.e. such that:

$$Q(\hat{\theta}^k; \hat{\theta}^{k-1}) + \log \mathbb{P}(\hat{\theta}^k) > Q(\hat{\theta}^{k-1}; \hat{\theta}^{k-1}) + \log \mathbb{P}(\hat{\theta}^{k-1}) \quad (6)$$

  subject to appropriate non-negativity and normalization constraints on parameters, and can be achieved via gradient-based methods (detailed procedure in Appendix A.2). We terminate when it becomes no longer possible to obtain a new estimate further improving the expected log-posterior—i.e. when the "M-step" cannot be performed. Algorithm 1 summarizes this learning procedure.

Algorithm 1 Bayesian INTERPOLE

Input: Dataset $\mathcal{D} = \{h^i_{\tau_i}\}^n_{i=1}$, prior $\mathbb{P}(\theta)$
Sample $\hat{\theta}^0$ from $\mathbb{P}(\theta)$
for $k = 1, 2, \ldots$ **do**
  Compute $\mathbb{P}(\bar{\mathcal{D}}|\mathcal{D}, \hat{\theta}^{k-1})$ ▷Appendix A.1
  Compute $\nabla_\theta Q(\theta; \hat{\theta}^{k-1})$ at $\hat{\theta}^{k-1}$ ▷Appendix A.2
  $\hat{\theta}^k \leftarrow \hat{\theta}^{k-1} + [\nabla_\theta Q(\theta; \hat{\theta}^{k-1}) + \nabla_\theta \log \mathbb{P}(\theta)]_{\theta=\hat{\theta}^{k-1}}$
until $\neg(6)$
Output: MAP estimate $\hat{\theta}^k \doteq (\hat{T}, \hat{O}, \hat{b}_1, \hat{\eta}, \{\hat{\mu}_a\}_{a\in A})$

Explaining by Imitating. Recall our original mandate—to give the *most plausible explanation* for behavior. Two questions can be asked about our proposal to "explain by imitating"—to which we now have precise answers: One concerns explainability, the other directness of explanations.

First, what constitutes the "most plausible explanation" of behavior? Now, INTERPOLE identifies this as the *most likely parameterization* of that behavior using a state-based model for beliefs and policies—but otherwise with no further assumptions. In particular, we are only positing that modeling beliefs over states helps provide an interpretable description of how an *agent* reasons (which we do have ample evidence for[2])—but we are not assuming that the *environment* itself takes the form of a state-based model (which is an entirely different claim). Mathematically, the complete likelihood (Equation 4) highlights the difference between decision dynamics (which help explain the agent's behavior) and "true" environment dynamics (which we do not care about). The latter are independent of the agent, and learning them would have involved just the observation likelihoods alone. In contrast, by *jointly* estimating T, O, b_1 with $\eta, \{\mu_a\}_{a\in A}$ according to *both* observation- and action-likelihoods, we are learning the decision dynamics—which in general need not coincide with the environment, but which offer the most plausible explanation of how the agent effectively reasons.

A second question is about *directness*: Given the popularity of IRL, could we have simply used an (indirect) reward parameterization, instead of our (direct) mean-vector parameterization? As it turns out, in addition to the "immediate" interpretability of direct, action-level representations, it comes with an extra perk w.r.t. computability: While it is (mathematically) possible to formulate a similar learning problem swapping out μ for rewards, in practice it is (computationally) intractable to perform in our setting. The precise difficulty lies in differentiating through quantities $\pi(a_t|b_t)$—which in turn depend on beliefs and dynamics—in the action-likelihoods (proofs are found in Appendix B):

[2] In healthcare, diseases are often modeled in terms of states, and beliefs over disease states are transparent factors that medical practitioners (i.e. the domain experts) readily comprehend and reason about [26, 27].

Proposition 1 *(Differentiability with q-Parameterizations)* Consider softmax policies parameterized by q-values from a reward function, such that $\pi(a|b) = e^{q_*(b,a)} / \sum_{a'} e^{q_*(b,a')}$ in lieu of Equation 2. Then differentiating through $\log \pi(a_t|b_t)$ terms with respect to unknown parameters θ is *intractable*.

In contrast, INTERPOLE avoids ever needing to solve any "forward" problems (therefore does not require resorting to costly—and approximate—sampling-based workarounds):

Proposition 2 *(Differentiability with μ-Parameterizations)* Consider the mean-vector policy parameterization proposed in Equation 2. Differentiation through the $\log \pi(a_t|b_t)$ terms with respect to the unknown parameters θ is easily and automatically performed by *backpropagation through time*.

5 ILLUSTRATIVE EXAMPLES

Three aspects of INTERPOLE deserve empirical demonstration, and our goal in this section is to highlight them in turn:

- *Interpretability:* First, we illustrate the usefulness of our method in providing transparent explanations of behavior. This is our primary objective——of explaining by imitating.
- *Accuracy:* Second, we demonstrate that faithfulness of learned policies is not given up for transparency. This shows accuracy and interpretability are not necessarily opposed.
- *Subjectivity:* Third, we show that INTERPOLE best recovers an agent's reasoning——even if that reasoning is biased. This sets us apart from alternative state-based algorithms.

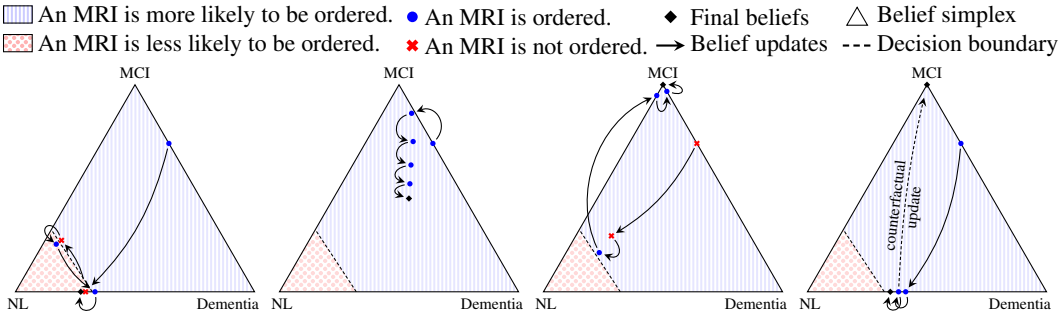
We show archetypical examples to exercise our framework, using both simulated and real-world experiments in the context of *disease diagnosis*. State-based reasoning is prevalent in research and practice: three states in progressive clinical dementia [28, 29], preterminal cancer screening [30, 31], or even—as recently shown—for cystic fibrosis [32] as well as for pulmonary disease [33].

Decision Environments. For our real-world setting, consider diagnostic patterns for 1,737 patients during sequences of 6-monthly visits in the Alzheimer's Disease Neuroimaging Initiative [34] database (**ADNI**). The state space consists of normal functioning ("NL"), mild cognitive impairment ("MCI"), and dementia. For the action space, we consider the decision problem of ordering vs. not ordering an MRI test, which—while often informative of Alzheimer's—is financially costly. MRI outcomes are per hippocampal volume: {"avg", "above avg", "below avg", "not ordered"}; separately, cognitive dementia rating-sum of boxes ("CDR-SB")—which is always measured—falls in: {"normal", "questionable impairment", "mild/severe dementia"} [28]. In total, the observations space therefore consists of the 12 outcome combinations.

We also consider a simulated setting to better validate performance. For this we employ a diagnostic environment (**DIAG**) in the form of an IOHMM with certain (true) parameters $T^{\text{true}}, O^{\text{true}}, b_1^{\text{true}}$. Patients fall within diseased (s_+) and healthy (s_-) states, and vital-sign measurements available at every step are classified within positive (z_+) and negative (z_-) outcomes. For the action space, we consider the decision of continuing to monitor a patient ($a_=$), or stopping and declaring a final diagnosis—and if so, a diseased (a_+) or healthy (a_-) declaration. If we assume agents have perfect knowledge of the true environment, then this setup is similar to the classic "tiger problem" for optimal stopping [35]. We also consider a (more realistic) variant of DIAG where the agent's behavior is instead generated by biased beliefs due to incorrect knowledge $T, O, b_1 \neq T^{\text{true}}, O^{\text{true}}, b_1^{\text{true}}$ of the environment (**BIAS**). This generates a testable version of real-life settings where decision-makers' (subjective) beliefs often fail to coincide with any (objective) probabilities.

Benchmark Algorithms. Where appropriate, we compare INTERPOLE against the following benchmarks: imitation by behavioral cloning [5] using RNNs for partial observability (**R-BC**); Bayesian IRL on POMDPs [9] equipped with a learned environment model (**PO-IRL**); a fully-offline counterpart [10] of Bayesian IRL (**Off. PO-IRL**); and an adaptation of model-based imitation learning [7] to partially-observable settings, with a learned IOHMM as the model (**PO-MB-IL**). Algorithms requiring learned models for interaction are given IOHMMs estimated using conventional methods [36]. Further information on environments and benchmarks is located in Appendix C.

Interpretability. First, we direct attention to the potential utility of INTERPOLE as an *investigative device* for auditing and quantifying individual decisions. Specifically, modeling the evolution of an agent's beliefs provides a concrete basis for analyzing the corresponding sequence of actions taken:



(a) **Typical Normal Patient** (b) **Typical Deteriorating Patient** (c) **Patient is Diagnosed Late** (d) **Patient with High-value Tests**

Figure 3: *Decision Trajectories*. Examples of real patients, including: (a) A typical normally-functioning patient, where beliefs remain mostly on the decision boundary. (b) A typical patient believed to be deteriorating towards dementia. (c) A patient who could have been diagnosed much earlier. (d) A patient with a (seemingly redundant) MRI test that is actually highly informative.

Table 2: *Performance Comparisons.* In ADNI, INTERPOLE is first- or second-best for all action-matching metrics. In DIAG and BIAS, INTERPOLE is best. Belief/policy mismatch is not applicable to ADNI without ground-truth beliefs/policies. Belief mismatch is not applicable to R-BC. $^{\dagger}\times 10^{-3}$

	ADNI			DIAG			BIAS		
Algorithm	**Calibration (Brier Score)**	**Area under ROC Curve**	**Area under PR Curve**	**Belief Mismatch**†	**Policy Mismatch**†	**Stopping Time Error**	**Belief Mismatch**†	**Policy Mismatch**†	**Stopping Time Error**
R-BC	0.18 ± 0.05	0.61 ± 0.05	0.81 ± 0.08	–	6.7 ± 1.4	5.91 ± 1.29	–	191.8 ± 78.8	2.22 ± 0.45
PO-MB-IL	0.19 ± 0.07	0.54 ± 0.07	0.79 ± 0.11	42.7 ± 34.0	47.9 ± 18.9	6.34 ± 1.48	83.2 ± 3.03	125.4 ± 18.4	3.80 ± 0.19
PO-IRL	0.23 ± 0.01	0.51 ± 0.07	0.78 ± 0.09	42.7 ± 34.0	62.1 ± 29.1	6.41 ± 1.80	83.2 ± 3.03	144.0 ± 29.4	3.46 ± 0.22
Off. PO-IRL	0.24 ± 0.01	0.54 ± 0.05	0.79 ± 0.09	26.1 ± 5.6	2.1 ± 0.2	5.42 ± 0.69	84.9 ± 8.28	62.8 ± 7.5	3.12 ± 0.41
INTERPOLE	0.17 ± 0.05	0.60 ± 0.04	0.81 ± 0.09	0.6 ± 0.1	0.8 ± 0.2	5.38 ± 1.14	3.8 ± 0.34	1.8 ± 0.6	2.14 ± 0.51

- *Explaining Trajectories*. Figure 3 shows examples of such decision trajectories for four real ADNI patients; each vertex of the belief simplex corresponds to one of the three stable diagnoses. Patients (a) and (b) are "typical" patients who fit well to the overall learned policy. The former is a normally-functioning patient believed to remain around the decision boundary in all visits except the first; appropriately, they are ordered an MRI approximately half the time. The latter is believed to be deteriorating from MCI towards dementia, hence prescribed an MRI in all visits.
- *Identifying Belated Diagnoses*. In many diseases, early diagnosis is paramount [37]. INTERPOLE allows detecting patients who appear to have been diagnosed significantly later than they should have. Patient (c) was ordered an MRI in neither of their first two visits—despite the fact that the "typical" policy would have strongly recommended one. At a third visit, the MRI that was finally ordered led to near-certainty of cognitive impairment—but this could have been known 12 months earlier! In fact, among all ADNI patients, 6.5% were subject to this pattern of "belatedness", where a late MRI is followed by a jump to near-certain deterioration.
- *Quantifying Value of Information*. Patient (d) highlights how INTERPOLE can be used to quantify the value of a test in terms of its information gain. While the patient was ordered an MRI in all visits, it may appear (on the surface) that the third and final MRIs were redundant—having little affect on beliefs. However, in this case the tests were in fact highly informative, since (as it happened) the patient's CDR-SB scores were suggestive of impairment, and (in the counterfactual) the doctor's beliefs could have potentially leapt drastically towards MCI. On the other hand, among all MRIs ordered for ADNI patients, 19% may indeed have been unnecessary (i.e. triggering insignificant belief-updates both factually and counterfactually).

Accuracy. Now a reasonable question is whether such explainability comes at a cost: By learning an interpretable policy, do we sacrifice any accuracy? To be precise, we can ask the following: (1) Is the *belief-update process* the same? For this, the error metric is the discrepancy w.r.t. the sequence of beliefs—which we take to be $\sum_t D_{\mathrm{KL}}(b_t \| \hat{b}_t)$ (**Belief Mismatch**). (2) Is the *belief-action* mapping the same? Our metric is the discrepancy w.r.t. the policy distribution itself—which we take to be $\sum_t D_{\mathrm{KL}}(\pi_{\mathrm{b}}(\cdot|b_t) \| \hat{\pi}(\cdot|\hat{b}_t))$ (**Policy Mismatch**). (3) Is the *effective behavior* the same? Here the error metrics are those that measure the discrepancy w.r.t. ground-truth actions observed

(**Action-Matching**) for ADNI, and differences in stopping (**Stopping Time Error**) for DIAG and BIAS. Note that action-matching and stopping time errors evaluate the quality of learned models in *imitating* per se, while belief and policy mismatch evaluate their quality in *explaining*.

The results are revealing, if not necessarily surprising. To begin, we observe for ADNI in Table 2 (in terms of action-matching) that INTERPOLE is first- or second-best in all metrics; where it comes second, it does so only slightly to R-BC—which is specifically optimized for nothing but action-matching. Similarly for DIAG (in terms of stopping time error), INTERPOLE performs the best, meaning little—if any—imitation accuracy is lost by using INTERPOLE as the policy model.

Perhaps more interestingly, we also see in Table 2 that the quality of internal explanations is superior—in terms of both belief mismatch and policy mismatch. In particular, even though comparators PO-MB-IL, PO-IRL, and Off. PO-IRL map decisions through beliefs, they inherit the conventional approach of attempting to estimate *true* environment dynamics, which is unnecessary—and possibly detrimental—if the goal is simply to find the *most likely* explanation of behavior. Interestingly, while the difference in imitation quality among benchmarks is not huge, for explanation quality the gap is significant—where INTERPOLE has great advantage.

Subjectivity. Most significantly, we now show that INTERPOLE recovers the best explanations, even if—or perhaps *especially* if—the agent is driven by subjective reasoning (i.e. with biased beliefs). This aspect sets INTERPOLE firmly apart from comparable state-based techniques. Consider the BIAS environment: Here the true environment dynamics are unchanged from DIAG, but no longer coincide with the agent's decision dynamics. Specifically, we let the behavioral policy be generated using erroneous parameters $O(z_-|a_=, s_+) < O^{\text{true}}(z_-|a_=, s_+)$; i.e. the doctor now believes the test to have a smaller *false-negative rate* than it really does—thus biasing their beliefs about patient states.

Now suppose we wish to recover the decision boundary from the demonstrations—that is, at what confidence threshold does a doctor commit to a healthy diagnosis? Figure 4 shows that both INTERPOLE and PO-MB-IL appear to recover the correct *effective behavior*: Starting from a neutral prior, doctors tend to stop and issue a "healthy" diagnosis if the first two observations return negative signals. Importantly, INTERPOLE also correctly locates the confidence target $\sim 90\%$. On the other hand, PO-MB-IL—which first attempts to estimate the environment's true parameters—ends up learning a policy on the basis of miscalibrated beliefs, thereby incorrectly explaining the same effective behavior with a lower confidence target $\sim 70\%$. Finally, through benchmarked metrics, Table 2 further confirms INTERPOLE's advantage in providing (correct) explanations.

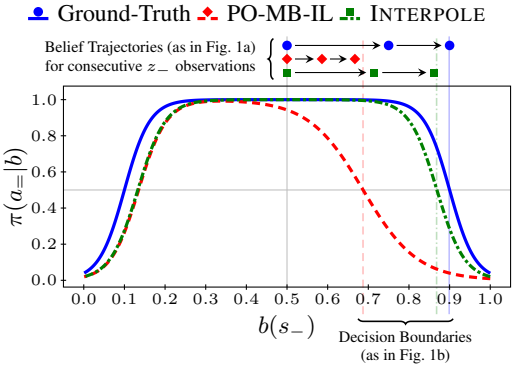


Figure 4: *Explaining Subjective Behavior.* Markers show the underlying belief trajectories when two negative (z_-) observations are made. While the effective behavior of all policies is similar, only INTERPOLE correctly identifies the ground-truth decision boundary. This shows the significance of distinguishing between decision dynamics (which help explain agents' behavior) and true dynamics (which we do not care about).

6 DISCUSSION

Two points deserve brief comment in closing. First, while we gave prominence to several examples of how INTERPOLE may be used to audit and improve decision-making behavior, the potential applications are not limited to these use cases. Broadly, the chief proposition is that having quantitative descriptions of belief trajectories provides a concrete language that enables investigating observed actions, including outliers and variations in behavior: On that basis, different statistics and post-hoc analyses can be performed on top of INTERPOLE's explanations (see Appendix C for examples).

It is crucial, however, to keep in mind that INTERPOLE does not claim to identify the real intentions of an agent: humans are complex, and rationality is of course bounded. What it does do, is to provide an interpretable explanation of how an agent is effectively behaving, which——as we have seen with ADNI patients——offers a yardstick by which to assess and compare trajectories and subgroups. In particular, INTERPOLE accomplishes this while adhering to our key criteria for healthcare settings, and without imposing assumptions of unbiasedness or optimality on behavioral policies.

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A DETAILS OF THE ALGORITHM

A.1 FORWARD-BACKWARD PROCEDURE

We compute the necessary marginalizations of the joint distribution $\mathbb{P}(\bar{\mathcal{D}}|\mathcal{D}, \hat{\theta})$ using the forward-backward algorithm. Letting $\boldsymbol{x}_{t:t'} = \{x_t, x_{t+1}, \ldots, x_{t'}\}$ for any time-indexed quantity x_t, the forward messages are defined as $\alpha_t(s) = \mathbb{P}(s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}|\hat{\theta})$, which can be computed dynamically as

$$\begin{aligned}
\alpha_{t+1}(s') &= \mathbb{P}(s_{t+1} = s', \boldsymbol{a}_{1:t}, \boldsymbol{z}_{1:t}|\hat{\theta}) \\
&= \sum_{s \in S} \mathbb{P}(s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}|\hat{\theta}) \mathbb{P}(s_{t+1} = s', a_t, z_t | s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}, \hat{\theta}) \\
&= \sum_{s \in S} \alpha_t(s) \hat{\pi}(a_t|b_t) \hat{T}(s'|s, a_t) \hat{O}(z_t|a_t, s') \\
&\propto \sum_{s \in S} \alpha_t(s) \hat{T}(s'|s, a_t) \hat{O}(z_t|a_t, s')
\end{aligned}$$

with initial case $\alpha_1(s) = \mathbb{P}(s_1 = s) = b_1(s)$. The backward messages are defined as $\beta_t(s) = \mathbb{P}(\boldsymbol{a}_{t:\tau}, \boldsymbol{z}_{t:\tau}|s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}, \hat{\theta})$, which can also be computed dynamically as

$$\begin{aligned}
\beta_t(s) &= \mathbb{P}(\boldsymbol{a}_{t:\tau}, \boldsymbol{z}_{t:\tau}|s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}, \hat{\theta}) \\
&= \sum_{s' \in S} \mathbb{P}(s_{t+1} = s', a_t, z_t | s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}, \hat{\theta}) \mathbb{P}(\boldsymbol{a}_{t+1:\tau}, \boldsymbol{z}_{t+1:\tau}|s_{t+1} = s', \boldsymbol{a}_{1:t}, \boldsymbol{z}_{1:t}, \hat{\theta}) \\
&= \sum_{s' \in S} \hat{\pi}(a_t|b_t) \hat{T}(s'|s, a_t) \hat{O}(z_t|a_t, s') \beta_{t+1}(s') \\
&\propto \sum_{s' \in S} \hat{T}(s'|s, a_t) \hat{O}(z_t|a_t, s') \beta_{t+1}(s')
\end{aligned}$$

with initial case $\beta_{\tau+1}(s) = \mathbb{P}(\emptyset|s_{\tau+1} = s, \boldsymbol{a}_{1:\tau}, \boldsymbol{z}_{1:\tau}, \hat{\theta}) = 1$.

Then, the marginal probability of being in state s at time t given the dataset $\mathcal{D}$ and the estimate $\hat{\theta}$ can be computed as

$$\begin{aligned}
\gamma_t(s) &= \mathbb{P}(s_t = s|\mathcal{D}, \hat{\theta}) \\
&= \mathbb{P}(s_t = s|\boldsymbol{a}_{1:\tau}, \boldsymbol{z}_{1:\tau}, \hat{\theta}) \\
&\propto \mathbb{P}(s_t = s, \boldsymbol{a}_{1:\tau}, \boldsymbol{z}_{1:\tau}|\hat{\theta}) \\
&= \alpha_t(s)\beta(s)
\end{aligned}$$

and similarly, the marginal probability of transitioning from state s to state s' at the end of time t given the dataset $\mathcal{D}$ and the estimate $\hat{\theta}$ can be computed as

$$\begin{aligned}
\xi_t(s, s') &= \mathbb{P}(s_t = s, s_{t+1} = s'|\mathcal{D}, \hat{\theta}) \\
&\propto \mathbb{P}(s_t = s, s_{t+1} = s', \boldsymbol{a}_{1:\tau}, \boldsymbol{z}_{1:\tau}|\hat{\theta}) \\
&= \mathbb{P}(s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}|\hat{\theta}) \mathbb{P}(s_{t+1} = s', a_t, z_t | s_t = s, \boldsymbol{a}_{1:t-1}, \boldsymbol{z}_{1:t-1}, \hat{\theta}) \\
&\qquad \times \mathbb{P}(\boldsymbol{a}_{t+1:\tau}, \boldsymbol{z}_{t+1:\tau}|s_{t+1} = s', \boldsymbol{a}_{1:t}, \boldsymbol{z}_{1:t}, \hat{\theta}) \\
&= \alpha_t(s) \hat{\pi}(a_t|b_t) \hat{T}(s'|s, a) \hat{O}(z|a, s') \beta_{t+1}(s') \\
&\propto \alpha_t(s) \hat{T}(s'|s, a) \hat{O}(z|a, s') \beta_{t+1}(s') \ .
\end{aligned}$$

A.2 GRADIENT-ASCENT PROCEDURE

Taking the gradient of the expected log-likelihood $Q(\theta; \hat{\theta})$ in (5) with respect to the unknown parameters $\theta = (T, O, b_1, \eta, \mu_{a \in A})$ first requires computing the Jacobian matrix $\nabla_{b_t} b_{t'}$ for $1 \leq$

$t < t' \leq \tau$, where $(\nabla_b b')_{ij} = \partial b'(i)/\partial b(j)$ for $i, j \in S$. This can be achieved dynamically as $\nabla_{b_t} b_{t'} = \nabla_{b_{t+1}} b_{t'} \nabla_{b_t} b_{t+1}$ with initial case $\nabla_{b_{t'}} b_{t'} = I$, where

$$
\begin{aligned}
(\nabla_{b_t} b_{t+1})_{ij} &= \frac{\partial b_{t+1}(i)}{\partial b_t(j)} \\
&= \frac{\partial}{\partial b_t(j)} \left[\frac{\sum_{x \in S} b_t(x) T(i|x, a_t) O(z_t|a_t, i)}{\sum_{x \in S} \sum_{x' \in S} b_t(x) T(x'|x, a_t) O(z_t|a_t, x')} \right] \\
&= \frac{T(i|j, a_t) O(z_t|a_t, i)}{\sum_{x \in S} \sum_{x' \in S} b_t(x) T(x'|x, a_t) O(z_t|a_t, x')} \\
&\qquad - \frac{\sum_{x' \in S} T(x'|j, a_t) O(z_t|a_t, x')}{(\sum_{x \in S} \sum_{x' \in S} b_t(x) T(x'|x, a_t) O(z_t|a_t, x'))^2} \,.
\end{aligned}
$$

A.2.1 Partial Derivatives

The derivative of $Q(\theta; \hat{\theta})$ with respect to $T(s'|s, a)$ is

$$
\begin{aligned}
\frac{\partial Q(\theta; \hat{\theta})}{\partial T(s'|s, a)} &= \frac{\partial}{\partial T(s'|s, a)} \sum_{i=1}^{n} \left[\sum_{t=1}^{\tau} \mathbb{I}\{a_t = a\} \sum_{x \in S} \sum_{x' \in S} \xi_t(x, x') \log T(x'|x, a) \right. \\
&\qquad \left. + \sum_{t=2}^{\tau} \log \pi(a_t|b_t) \right] \\
&= \sum_{i=1}^{n} \left[\sum_{t=1}^{\tau} \mathbb{I}\{a_t = a\} \frac{\xi_t(s, s')}{T(s'|s, a)} + \sum_{t=2}^{\tau} \frac{\partial \log \pi(a_t|b_t)}{\partial T(s'|s, a)} \right] \\
&= \sum_{i=1}^{n} \left[\sum_{t=1}^{\tau} \mathbb{I}\{a_t = a\} \frac{\xi_t(s, s')}{T(s'|s, a)} \right. \\
&\qquad \left. + \sum_{t=2}^{\tau} \sum_{t'=1}^{t-1} \nabla_{b_t} \log \pi(a_t|b_t) \nabla_{b_{t'+1}} b_t \nabla_{T(s'|s,a)} b_{t'+1} \right] \,,
\end{aligned}
$$

where

$$
\begin{aligned}
(\nabla_{b_t} \log \pi(a_t|b_t))_{1j} &= \frac{\partial \log(a_t|b_t)}{\partial b_t(j)} \\
&= \frac{\partial}{\partial b_t(j)} \left(-\eta \|b_t - \mu_{a_t}\|^2 - \log \sum_{a' \in A} e^{-\eta \|b_t - \mu_{a'}\|^2} \right) \\
&= -2\eta(b_t(j) - \mu_{a_t}(j)) + 2\eta \sum_{a \in A} \frac{e^{-\eta \|b_t - \mu_a\|^2}}{\sum_{a' \in A} e^{-\eta \|b_t - \mu_{a'}\|^2}} (b_t(j) - \mu_a(j)) \\
&= -2\eta(b_t(j) - \mu_{a_t}(j)) + 2\eta \sum_{a \in A} \pi(a|b_t)(b_t(j) - \mu_a(j))
\end{aligned}
$$

and

$$
\begin{aligned}
(\nabla_{T(s'|s,a)} b_{t'+1})_{i1} &= \frac{\partial b_{t'+1}(i)}{\partial T(s'|s, a)} \\
&= \frac{\partial}{\partial T(s'|s, a)} \left(\frac{\sum_{x \in S} b_{t'}(x) T(i|x, a_{t'}) O(z_{t'}|a_{t'}, i)}{\sum_{x \in S} \sum_{x' \in S} b_{t'}(x) T(x'|x, a_{t'}) O(z_{t'}|a_{t'}, x')} \right) \\
&= \mathbb{I}\{a_{t'} = a\} \left(\frac{\mathbb{I}\{i = s'\} b_{t'}(s) O(z_{t'}|a, s')}{\sum_{x \in S} \sum_{x' \in S} b_{t'}(x) T(x'|x, a) O(z_{t'}|a, x')} \right. \\
&\qquad \left. - \frac{b_{t'}(s) O(z_{t'}|a, s')}{(\sum_{x \in S} \sum_{x' \in S} b_{t'}(x) T(x'|x, a) O(z_{t'}|a, x'))^2} \right) \,.
\end{aligned}
$$

The derivative of $Q(\theta; \hat{\theta})$ with respect to $O(z|a, s')$ is

$$
\frac{\partial Q(\theta; \hat{\theta})}{\partial O(z|a, s')} = \frac{\partial}{\partial O(z|a, s')} \sum_{i=1}^{n} \left[\sum_{t=1}^{\tau} \mathbb{I}\{a_t = a, z_t = z\} \sum_{x' \in S} \gamma_{t+1}(x') \log O(z|a, x') \right.
$$

$$
\begin{aligned}
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad + \sum_{t=2}^{\tau} \log \pi(a_t|b_t) \Bigg] \\
&= \sum_{i=1}^{n} \left[\sum_{t=1}^{\tau} \mathbb{I}\{a_t = a, z_t = z\} \frac{\gamma_{t+1}(s')}{O(z|a,s')} + \sum_{t=2}^{\tau} \frac{\partial \log \pi(a_t|b_t)}{\partial O(z|a,s')} \right] \\
&= \sum_{i=1}^{n} \Bigg[\sum_{t=1}^{\tau} \mathbb{I}\{a_t = a, z_t = z\} \frac{\gamma_{t+1}(s')}{O(z|a,s')} \\
&\qquad\qquad + \sum_{t=2}^{\tau} \sum_{t'=1}^{t-1} \nabla_{b_t} \log \pi(a_t|b_t) \nabla_{b_{t'+1}} b_t \nabla_{O(z|a,s')} b_{t'+1} \Bigg] ,
\end{aligned}
$$

where

$$
\begin{aligned}
(\nabla_{O(z|a,s')} b_{t'+1})_{i1} &= \frac{\partial b_{t'+1}(i)}{\partial O(z|a,s')} \\
&= \frac{\partial}{\partial O(z|a,s')} \left(\frac{\sum_{x \in S} b_{t'}(x) T(i|x,a_{t'}) O(z_{t'}|a_{t'},i)}{\sum_{x \in S} \sum_{x' \in S} b_{t'}(x) T(x'|x,a_{t'}) O(z_{t'}|a_{t'},x')} \right) \\
&= \mathbb{I}\{a_{t'} = a, z_{t'} = z\} \Bigg(\frac{\mathbb{I}\{i = s'\} \sum_{x \in S} b_{t'}(x) T(s'|x,a)}{\sum_{x \in S} \sum_{x' \in S} b_{t'}(x) T(x'|x,a) O(z|a,x')} \\
&\qquad\qquad - \frac{\sum_{x \in S} b_{t'}(x) T(s'|x,a)}{(\sum_{x \in S} \sum_{x' \in S} b_{t'}(x) T(x'|x,a) O(z|a,x'))^2} \Bigg) .
\end{aligned}
$$

The derivative of $Q(\theta; \hat{\theta})$ with respect to $b_1(s)$ is

$$
\begin{aligned}
\frac{\partial Q(\theta; \hat{\theta})}{\partial b_1(s)} &= \frac{\partial}{\partial b_1(s)} \sum_{i=1}^{n} \left[\sum_{x \in S} \gamma_1(x) \log b_1(x) + \sum_{t=1}^{\tau} \log \pi(a_t|b_t) \right] \\
&= \sum_{i=1}^{n} \left[\frac{\gamma_1(s)}{b_1(s)} + \sum_{t=1}^{\tau} \nabla_{b_t} \log \pi(a_t|b_t) \nabla_{b_1(s)} b_t \right] ,
\end{aligned}
$$

where $(\nabla_{b_1(s)} b_t)_{i1} = (\nabla_{b_1} b_t)_{is}$.

The derivative of $Q(\theta; \hat{\theta})$ with respect to η is

$$
\begin{aligned}
\frac{\partial Q(\theta; \hat{\theta})}{\partial \eta} &= \frac{\partial}{\partial \eta} \sum_{i=1}^{n} \sum_{t=1}^{\tau} \log \pi(a_t|b_t) \\
&= \sum_{i=1}^{n} \sum_{t=1}^{\tau} \frac{\partial}{\partial \eta} \left(-\eta \|b_t - \mu_{a_t}\|^2 - \log \sum_{a' \in A} e^{-\eta \|b_t - \mu_{a'}\|^2} \right) \\
&= \sum_{i=1}^{n} \sum_{t=1}^{\tau} \left(-\|b_t - \mu_{a_t}\|^2 + \sum_{a \in A} \frac{e^{-\eta \|b_t - \mu_a\|^2}}{\sum_{a' \in A} e^{-\eta \|b_t - \mu_{a'}\|^2}} \|b_t - \mu_a\|^2 \right) \\
&= \sum_{i=1}^{n} \sum_{t=1}^{\tau} \left(-\|b_t - \mu_{a_t}\|^2 + \sum_{a \in A} \pi(a|b_t) \|b_t - \mu_a\|^2 \right) .
\end{aligned}
$$

Finally, the derivative of $Q(\theta; \hat{\theta})$ with respect to $\mu_a(s)$ is

$$
\begin{aligned}
\frac{\partial Q(\theta; \hat{\theta})}{\partial \mu_a(s)} &= \frac{\partial}{\partial \mu_a(s)} \sum_{i=1}^{n} \sum_{t=1}^{\tau} \log \pi(a_t|b_t) \\
&= \sum_{i=1}^{n} \sum_{t=1}^{\tau} \frac{\partial}{\partial \mu_a(s)} \left(-\eta \|b_t - \mu_{a_t}\|^2 - \log \sum_{a' \in A} e^{-\eta \|b_t - \mu_{a'}\|^2} \right) \\
&= \sum_{i=1}^{n} \sum_{t=1}^{\tau} \left(2\eta \mathbb{I}\{a_t = a\}(b_t(s) - \mu_a(s)) - 2\eta \frac{e^{-\eta \|b_t - \mu_a\|^2}}{\sum_{a' \in A} e^{-\eta \|b_t - \mu_{a'}\|^2}} (b_t(s) - \mu_a(s)) \right)
\end{aligned}
$$

$$= \sum_{i=1}^{n} \sum_{t=1}^{\tau} (2\eta \mathbb{I}\{a_t = a\}(b_t(s) - \mu_a(s)) - 2\eta\pi(a|b_t)(b_t(s) - \mu_a(s))$$
$$= \sum_{i=1}^{n} \sum_{t=1}^{\tau} 2\eta(\mathbb{I}\{a_t = a\} - \pi(a|b_t))(b_t(s) - \mu_a(s)) \ .$$

B Proofs of Propositions

B.1 Proof of Proposition 1

First, denote with $q_R^* \in \mathbb{R}^{\Delta(S)\times A}$ the optimal (belief-state) q-value function with respect to the underlying (state-space) reward function $R \in \mathbb{R}^{S\times A}$, and denote with $v^* \in \mathbb{R}^{\Delta(S)}$ the corresponding optimal value function $v_R^*(b) = \mathrm{softmax}_{a'\in A}\, q_R^*(b, a')$. Now, fix some component i of parameters θ; we wish to compute the derivative of $\log \pi(a|b)$ with respect to θ_i:

$$\begin{aligned}
\frac{\partial}{\partial\theta_i} \log \pi(a|b) &= \frac{\partial}{\partial\theta_i} \left(q_R^*(b, a) - v_R^*(b)\right) \\
&= \frac{\partial}{\partial\theta_i} \left(q_R^*(b, a) - \log \sum_{a'\in A} e^{q_R^*(b,a')}\right) \\
&= \frac{\partial}{\partial\theta_i} q_R^*(b, a) - \sum_{a'\in A} \left(\frac{e^{q_R^*(b,a')}}{\sum_{a''\in A} e^{q_R^*(b,a'')}} \cdot \frac{\partial}{\partial\theta_i} q_R^*(b, a')\right) \\
&= \frac{\partial}{\partial\theta_i} q_R^*(b, a) - \sum_{a'\in A} \pi(a'|b) \frac{\partial}{\partial\theta_i} q_R^*(b, a') \\
&= \frac{\partial}{\partial\theta_i} q_R^*(b, a) - \mathbb{E}_{a'\sim\pi(\cdot|b)} \left[\frac{\partial}{\partial\theta_i} q_R^*(b, a')\right]
\end{aligned}$$

where we make explicit here the dependence on R, but note that it is itself a parameter; that is, $R = \theta_j$ for some j. We see that this in turn requires computing the partial derivative $\partial q_R^*(b, a)/\partial\theta_i$. Let γ be some appropriate discount rate, and denote with $\rho_R \in \mathbb{R}^{\Delta(S)\times A}$ the effective (belief-state) reward $\rho_R(b, a) \doteq \sum_{s\in S} b(s)R(s, a)$ corresponding to R. Further, let

$$\begin{aligned}
&\mathbb{P}(b'|b, a) \\
&\quad = \sum_{z\in Z} \mathbb{P}(z|b, a)\mathbb{P}(b'|b, a, z) \\
&\quad = \sum_{z\in Z} \left(\sum_{s\in S} \sum_{s'\in S} b(s)T(s'|s, a)O(z|a, s')\right) \delta\left(b' - \frac{\sum_{s\in S} b(s)T(\cdot|s, a)O(z|a, \cdot)}{\sum_{s\in S}\sum_{s'\in S} b(s)T(s'|s, a)O(z|a, s')}\right)
\end{aligned}$$

denote the (belief-state) transition probabilities induced by T and O, where δ is the Dirac delta function that returns one if the belief-update (Equation 1) returns b', and returns zero otherwise. Then the partial $\partial q_R^*(b, a)/\partial\theta_i$ is given as follows:

$$\begin{aligned}
\frac{\partial}{\partial\theta_i} q_R^*(b, a) &= \frac{\partial}{\partial\theta_i} \left(\rho_R(b, a) + \gamma \int_{b'\in\Delta(S)} \mathbb{P}(b'|b, a) v_R^*(b') db'\right) \\
&= \underbrace{\frac{\partial}{\partial\theta_i} \rho_R(b, a) + \gamma \int_{b'\in\Delta(S)} v_R^*(b') \frac{\partial}{\partial\theta_i} \mathbb{P}(b'|b, a) db'}_{\rho_{R,i}(b,a)} \\
&\qquad + \gamma \int_{b'\in\Delta(S)} \mathbb{P}(b'|b, a) \mathbb{E}_{a'\sim\pi(\cdot|b')} \left[\frac{\partial}{\partial\theta_i} q_R^*(b', a')\right] db'
\end{aligned}$$

from which we observe that $\partial q_R^*(b, a)/\partial\theta_i$ is a fixed point of a certain Bellman-like operator. Specifically, fix any function $f \in \mathbb{R}^{\Delta(S)\times A}$; then $\partial q_R^*(b, a)/\partial\theta_i$ is the fixed point of the operator

$\mathcal{T}^{\pi}_{R,i} : \mathbb{R}^{\Delta(S)\times A} \to \mathbb{R}^{\Delta(S)\times A}$ defined as follows:

$$(\mathcal{T}^{\pi}_{R,i} f)(b,a) = \rho_{R,i}(b,a) + \gamma \int_{b'\in\Delta(S)} \mathbb{P}(b'|b,a) \sum_{a'} \pi(a'|b') f(b',a') db'$$

which takes the form of a "generalized" Bellman operator on q-functions for POMDPs, where for brevity here we have written $\rho_{R,i}(b,a)$ to denote the expression $\frac{\partial}{\partial\theta_i}\rho_R(b,a) + \gamma \int_{b'\in\Delta(S)} v^*_R(b') \frac{\partial}{\partial\theta_i}\mathbb{P}(b'|b,a)db'$. Mathematically, this means that a recursive procedure can in theory be defined—cf. "∇q-iteration", analogous to q-iteration; see e.g. [38]—that may converge on the gradient under appropriate conditions. Computationally, however, this also means that taking a single gradient is at least as hard as solving POMDPs in general.

Further, note that while typical POMDP solvers operate by taking advantage of the convexity property of $\rho_R(b,a)$—see e.g. [39]—here there is no such property to make use of: In general, it is *not* the case that $\rho_{R,i}(b,a)$ is convex. To see this, consider the following counterexample: Let $S \doteq \{s_-, s_+\}$, $A \doteq \{a_=\}$, $Z \doteq \{z_-, z_+\}$, $T(s_-|s_-,a_=) = T(s_+|s_+,a_=) = p = 1$, $O(z_-|a_=,s_-) = O(z_+|a_=,s_+) = 1/4$, $b_1(s_+) = 1/2$, $R(s_-,a_=) = 0$, $R(s_+,a_=) = 1/2$, and $\gamma = 1/2$. For simplicity, we will simply write b instead of $b(s_+)$. Note that:

$$\begin{aligned}
q^*_R(b,a_=) &= b\sum_{t=0}\gamma^t R(s_+,a_=) + (1-b)\sum_{t=0}\gamma^t R(s_-,a_=) = b \\
v^*_R(b) &= \log \sum_{a\in\{a_=\}} e^{q^*_R(b,a)} = \log e^{q^*_R(b,a_=)} = q^*_R(b,a_=) = b \\
\mathbb{P}(z_+|b,a_=) &= \frac{1}{4}(bp + (1-b)(1-p)) + \frac{3}{4}(b(1-p) + (1-b)p) = \frac{1}{4}b + \frac{3}{4}(1-b) \\
\mathbb{P}(z_-|b,a_=) &= \frac{1}{4}(b(1-p) + (1-b)p) + \frac{3}{4}(bp + (1-b)(1-p)) = \frac{1}{4}(1-b) + \frac{3}{4}b \\
b'|b,a_=,z_+ &= \frac{\mathbb{P}(s'=s_+,z_+|b,a_=)}{\mathbb{P}(z_+|b,a_=)} = \frac{\frac{1}{4}bp + \frac{3}{4}(1-b)(1-p)}{\mathbb{P}(z_+|b,a_=)} = \frac{\frac{1}{4}b}{\frac{1}{4}b + \frac{3}{4}(1-b)} \\
b'|b,a_=,z_- &= \frac{\mathbb{P}(s'=s_+,z_-|b,a_=)}{\mathbb{P}(z_-|b,a_=)} = \frac{\frac{1}{4}(1-b)(1-p) + \frac{3}{4}bp}{\mathbb{P}(z_-|b,a_=)} = \frac{\frac{3}{4}b}{\frac{1}{4}(1-b) + \frac{3}{4}b} \\
\mathbb{P}(b'|b,a_=) &= \begin{cases} \mathbb{P}(z_+|b,a_=) & \text{if } b' = b'|b,a_=,z_+ \\ \mathbb{P}(z_-|b,a_=) & \text{if } b' = b'|b,a_=,z_- \\ 0 & \text{otherwise} \end{cases}
\end{aligned}$$

Now, let the elements of θ be ordered such that p is the i-th element, and consider $\rho_{R,i}(b,a)$—evaluated at $p = 1$:

$$\begin{aligned}
\rho_{R,i}(b,a_=) &\doteq \frac{\partial}{\partial p}\rho_R(b,a_=) + \gamma \int_{b'\in\Delta(S)} v^*_R(b') \frac{\partial}{\partial p}\mathbb{P}(b'|b,a_=)db' \\
&= \frac{1}{2}\left(v^*_R(b'|b,a_=,z_+)\frac{\partial}{\partial p}\mathbb{P}(z_+|b,a_=) + v^*_R(b'|b,a_=,z_-)\frac{\partial}{\partial p}\mathbb{P}(z_-|b,a_=)\right) \\
&= \frac{1}{2}\left(\frac{\frac{1}{4}b}{\frac{1}{4}b + \frac{3}{4}(1-b)}\left(\frac{1}{4}b - \frac{1}{4}(1-b) - \frac{3}{4}b + \frac{3}{4}(1-b)\right)\right. \\
&\qquad \left. + \frac{\frac{3}{4}b}{\frac{1}{4}(1-b) + \frac{3}{4}b}\left(-\frac{1}{4}b + \frac{1}{4}(1-b) + \frac{3}{4}b - \frac{3}{4}(1-b)\right)\right)
\end{aligned}$$

Clearly $\rho_{R,i}(b,a_=)$ cannot be convex since $\rho_{R,i}(1/2,a_=) = 0$ and $\rho_{R,i}(1,a_=) = 0$ but $\rho_{R,i}(3/4,a_=) > 0$.

B.2 Proof of Proposition 2

In contrast, unlike the indirect q-value parameterization above (which by itself requires approximate solutions to optimization problems), the mean-vector parameterization of INTERPOLE maps beliefs

directly to distributions over actions. Now, the derivatives of $\log \pi(a|b)$ are given as closed-form expressions in Appendices A.1 and A.2.

In particular, note that each b_t is computed through a feed-forward structure, and therefore can easily be differentiated with respect to the unknown parameters θ through backpropagation through time: Each time step leading up to an action corresponds to a "hidden layer" in a neural network, and the initial belief corresponds to the "features" that are fed into the network; the transition and observation functions correspond to the weights between layers, the the beliefs at each time step correspond to the activations between layers, the actions themselves correspond to class labels, and the action likelihood corresponds to the loss function (see Appendices A.1 and A.2).

Finally, note that computing all of the forward-backward messages α_t and β_t in Appendix A.1 has complexity $O(n\tau S^2)$, computing all of the Jacobian matricies $\nabla_{b_t} b_{t'}$ in Appendix A.2 has complexity $O(n\tau^2 S^3)$, and computing all of the partial derivatives given in Appendix A.2 has complexity at most $O(n\tau^2 S^2 AZ)$. Hence, fully differentiating the expected log-likelihood $Q(\theta; \hat{\theta})$ with respect to the unknown parameters θ has an overall (polynomial) complexity $O(n\tau^2 S^2 \max\{S, AZ\})$.

C Experiment Particulars

C.1 Details of Decision Environments

ADNI. We have filtered out visits without a CDR-SB measurement, which is almost always taken, and visits that do not occur immediately after the six-month period following the previous visit but instead occur after 12 months or later. This filtering leaves 1,626 patients with typically three consecutive visits each. For MRI outcomes, average is considered to be within half a standard deviation of the population mean. Since there are only two actions in this scenario, we have set $\eta = 1$ and relied on the distance between the two means to adjust for the stochasticity of the estimated policy—closer means being somewhat equivalent to a smaller η.

DIAG. We set $T^{\text{true}}(s_-|s_-, \cdot) = T^{\text{true}}(s_+|s_+, \cdot) = 1$, meaning patients do not heal or contract the diseases as the diagnosis progresses, $O^{\text{true}}(z_-|a_=, s_+) = O^{\text{true}}(z_+|a_=, s_-) = 0.4$, meaning measurements as a test have a false-negative and false-positive rates of 40%, and $b_1^{\text{true}}(s_+) = 0.5$. Moreover, the behavior policy is given by $T = T^{\text{true}}$, $O = O^{\text{true}}$, $b_1 = b_1^{\text{true}}$, $\eta = 10$, $\mu_{a_=}(s_+) = 0.5$, and $\mu_{a_-}(s_-) = \mu_{a_+}(s_+) = 1.3$. Intuitively, doctors continue monitoring the patient until they are 90% confident in declaring a final diagnosis. In this scenario, T and η are assumed to be known. The behavior dataset is generated as 100 demonstration trajectories.

BIAS. We set all parameters exactly the same way we did in DIAG with one important exception: now $O(s_-|a_=, z_+) = 0.2$ while it is still the case that $O^{\text{true}}(z_-|a_=, s_+) = 0.4$, meaning $O \neq O^{\text{true}}$ anymore. In this scenario, b_1 is also assumed to be known (in addition to T and η) to avoid any invariances between b_1 and O that we have encountered during training. The behavioral dataset is generated as 1000 demonstration trajectories.

C.2 Details of Benchmark Algorithms

R-BC. We train an RNN whose inputs are the observed histories h_t and whose outputs are the predicted probabilities $\hat{\pi}(a|h_t)$ of taking action a given the observed history h_t. The network consists of an LSTM unit of size 64 and a fully-connected hidden layer of size 64. We minimize the cross-entropy loss $\mathcal{L} = -\sum_{i=1}^{n} \sum_{t=1}^{\tau} \sum_{a \in A} \mathbb{I}\{a_t = a\} \log \hat{\pi}(a|h_t)$ using Adam optimizer with learning rate 0.001 until convergence, that is when the cross-enropy loss does not improve for 100 consecutive iterations.

PO-IRL. The IOHMM parameters T, O, and b_1 are initialized by sampling them uniformly at random. Then, they are estimated and fixed using conventional IOHMM methods. The reward parameter R is initialized as $\hat{R}^0(s, a) = \varepsilon_{s,a}$ where $\varepsilon_{s,a} \sim \mathcal{N}(0, 0.001^2)$. Then, it is estimated via Markov chain Monte Carlo (MCMC) sampling, during which new candidate samples are generated by adding Gaussian noise with standard deviation 0.001 to the last sample. A final estimate is formed by averaging every tenth sample among the second set of 500 samples, ignoring the first 500 samples. In order to compute optimal q-values, we have used an off-the-shelf POMDP solver available at `https://www.pomdp.org/code/index.html`.

Off. PO-IRL. All parameters are initialized exactly the same way as in PO-IRL. Then, both the IOHMM parameters T, O, and b_1, and the reward parameter R are estimated jointly via MCMC sampling. When generating new candidate samples, with eqaul probabilities, we have either sampled new T, O, and b_1 from IOHMM posterior (without changing R) or obtained a new R the same way we did in PO-IRL (without changing T, O, and b_1). A final estimate is formed the same way as in PO-IRL.

PO-MB-IL. The IOHMM parameters T, O, and b_1 are initialized by sampling them uniformly at random. Then, they are estimated and fixed using conventional IOHMM methods. Given the IOHMM parameters, we parameterized policies the same way we did in INTERPOLE, that is as described in (2). The policy parameters $\{\mu_a\}_{a \in A}$ are initialized as $\hat{\mu}_a^0(s) = (1/|S| + \varepsilon_{a,s}) / \sum_{s' \in S}(1/|S| + \varepsilon_{a,s'})$ where $\varepsilon_{a,s'} \sim \mathcal{N}(0, 0.001^2)$. Then, they are estimated according solely to the action likelihoods in (4) using the EM algorithm. The expected log-posterior is maximized using Adam optimizer with learning rate 0.001 until convergence, that is when the expected log-posterior does not improve for 100 consecutive iterations.

INTERPOLE. All parameters are initialized exactly the same way as in PO-MB-IL. Then, the IOHMM parameters T, O, and b_1, and the policy parameters $\{\mu_a\}_{a \in A}$ are estimated jointly according to both the action likelihoods and the observation likelihoods in (4). The expected log-posterior is again maximized using Adam optimizer with learning rate 0.001 until convergence.

C.3 FURTHER EXAMPLE: POST-HOC ANALYSES

Policy representations learned by INTEPOLE provide statisticians with means to derive concrete criteria that describe observed behavior in objective terms. These criteria, in turn, enable the quantitative analyses of the behavior using conventional statistical methods. For ADNI, we have considered two such criteria: *belatedness* of individual diagnoses and *informativeness* of individual tests.

Formally, the final diagnoses of a patient is said to be belated if (i) the patient was not ordered an MRI in one of their visits despite the fact that an MRI being ordered was the most likely outcome according to the policy estimated by INTERPOLE and (ii) the patient was ordered an MRI in a later visit that led to a near-certain diagnosis with at least 90% confidence according to the underlying beliefs estimated by INTERPOLE. An MRI is said to be uninformative if it neither (factually) caused nor could have (counterfactually) caused a significant change in the underlying belief-state of the patient, where an insignificant change is half a standard deviation less than the mean factual change in beliefs estimated by INTERPOLE.

Having defined belatedness and informativeness, one can investigate the frequency of belated diagnoses and uninformative MRIs in different cohorts of patients to see how practice varies between one cohort to another. In Table 3, we do so for six cohorts: all of the patients, patients who are over 75 years old, patients with apoE4 risk factor for dementia, patients with signs of MCI or dementia since their very first visit, female patients, and male patients. For instance, we see that uninformative MRIs are much more prevalent among patients with signs of MCI or dementia since their first visit. This could potentially be because these patients are monitored much more closely than usual given their condition.

Table 3: Frequency of belated diagnoses and uninformative MRIs in various patient cohorts.

Cohort	**Frequency of belated diagnoses**	**Frequency. of uninformative MRIs**
All patients	6.52%	18.8%
Patients over 75 years old	9.29%	18.1%
Patients with apoE4 risk factor	8.75%	19.3%
Patients with signs of MCI/dementia	9.26%	26.1%
Female patients	7.19%	17.6%
Male patients	5.97%	19.8%

Alternatively, one can divide patients into cohorts based on whether they have a belated diagnoses or an uninformative MRI to see which features these criteria correlate with more. We do so in

Table 4. For instance, we see that a considerable percentage of belated diagnoses are seen among male patients.

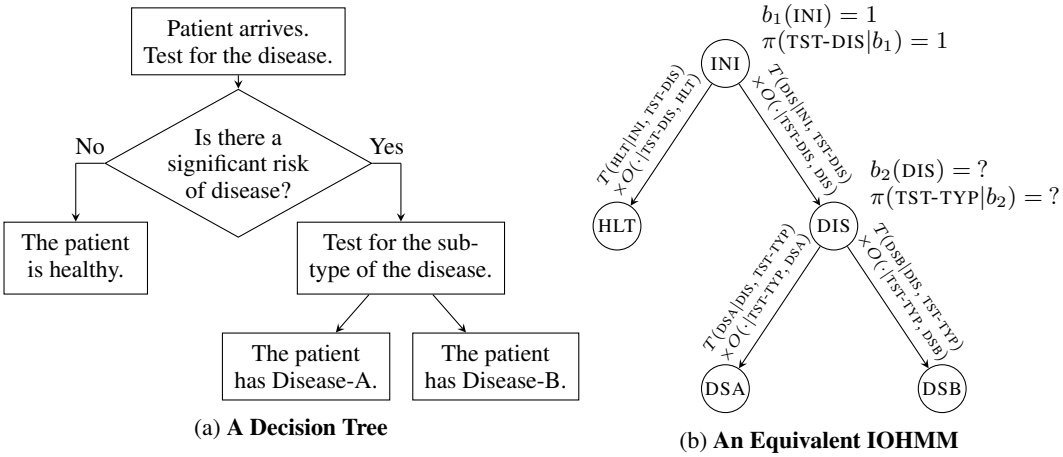
Table 4: Features of patients with belated diagnoses and uninformative MRIs.

Feature	**All patients**	**Patients with belated diagnoses**	**Patients with uninformative MRIs**
Mean age	73.9 ± 7.1	75.8 ± 7.5	73.0 ± 7.3
Freq. of apoE4	45.7%	54.2%	49.0%
Freq. of MCI/dementia signs	68.4%	95.8%	98.1%
Perc. of female patients	45.4%	39.0%	43.5%
Perc. of male patients	54.6%	61.0%	56.5%

C.4 Further Example: Decision Trees

Clinical practice guidelines are often given in the form of decision trees, which usually have vague elements that require the judgement of the practitioner [40, 41]. For example, the guideline could ask the practitioner to quantify risks, side effects, or improvements in subjective terms such as being significant, serious, or potential. Using direct policy learning, how vague elements like these are commonly resolved in practice can be learned in objective terms.

Formulating policies in terms of IOHMMs and decision boundaries is expressive enough to model decision trees. An IOHMM with deterministic observations, that is $O(z|a, s') = 1$ for some $z \in Z$ and for all $a \in A, s \in S$, essentially describes a finite-state machine, inputs of which are equivalent to the observations. Similarly, a deterministic decision tree can be defined as a finite-state machine with no looping sequence of transitions. The case where the observations are probabilistic rather than deterministic correspond to the case where the decision tree is traversed in a probabilistic way so that each path down the tree has a probability associated with it at each step of the traversal.



(a) **A Decision Tree** (b) **An Equivalent IOHMM**

Figure 5: *Two Different Descriptions of the Same Policy:* (a) in the form of a decision tree and (b) in terms of an equivalent IOHMM. For the IOHMM in (b), arrows denote possible transitions, where the probability of a transition is proportional to the quantity written above the corresponding arrow. Using direct policy learning, we can infer the risk of disease, $b_2(\text{DIS})$, and the probability of testing for the sub-type based on the risk, $\pi(\text{TST-TYP}|b_2)$, which are left vague in (a).

As a concrete example of modeling decision trees in terms of IOHMMs, consider the scenario of diagnosing a disease with two sub-types: Disease-A and Disease-B. Figure 5a depicts the policy of the doctors in the form of a decision tree. Each newly-arriving patient is first tested for the disease in a general sense without any distinction between the two sub-types it has. The patient is then tested for a specific sub-type of the disease only if the doctors deem there is a significant risk that the patient is diseased. Note that which exact level of confidence constitutes as a significant risk is left vague in

the decision tree. By modeling this scenario using our framework, we can learn: (i) how the risk is determined based on initial test results and (ii) what amount of risk is considered significant enough to require a subsequent test for the sub-type.

Let $S = \{\text{INI}, \text{HLT}, \text{DIS}, \text{DSA}, \text{DSB}\}$, where INI denotes that the patient has newly arrived, HLT denotes that the patient is healthy, DIS denotes that the patient is diseased, DSA denotes that the patient has Disease-A, and DSB denotes that the patient has Disease-B. Figure 5b depicts the state space S with all possible transitions. Note that the initial belief b_1 is such that $b_1(\text{INI}) = 1$. Let $A = \{\text{TST-DIS}, \text{TST-TYP}, \text{STP-HLT}, \text{STP-DSA}, \text{STP-DSB}\}$, where TST-DIS denotes testing for the disease, TST-TYP denotes testing for the sub-type of the disease, and the remaining actions denote stopping and diagnosing the patient with one of the terminal states, namely states HLT, DSA, and DSB.

After taking action $a_1 = \text{TST-DIS}$ and observing some initial test result $z_1 \in Z$, the risk of disease, which is the probability that the patient is diseased, can be calculated with a simple belief update:

$$\begin{aligned} b_2(\text{DIS}) &\propto \sum_{s \in S} b_1(s) T(\text{DIS}|s, \text{TST-DIS}) O(z_1|\text{TST-DIS}, \text{DIS}) \\ &= T(\text{DIS}|\text{INI}, \text{TST-DIS}) O(z_1|\text{TST-DIS}, \text{DIS}) \ . \end{aligned}$$

Moreover, we can say that the doctors are more likely to test for the sub-type of the disease as opposed to stopping and diagnosing the patient as healthy, that is $\pi_b(\text{TST-TYP}|b_2) > \pi_b(\text{STP-HLT}|b_2)$, when

$$b_2(\text{DIS}) > \frac{\mu_{\text{TST-TYP}}(\text{DIS}) + \mu_{\text{STP-HLT}}(\text{DIS})}{2}$$

assuming $\mu_{\text{TST-TYP}}(\text{DIS}) > \mu_{\text{STP-HLT}}(\text{DIS})$. Note that there are only two possible actions at the second time step: actions TST-TYP and STP-HLT.

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