

A Bayesian Model of Imitation in Infants and Robots

Rajesh P. N. Rao¹, Aaron P. Shon¹, and Andrew N. Meltzoff²

¹Department of Computer Science & Engineering

²Institute for Learning and Brain Sciences

University of Washington

Seattle, WA 98195

rao@cs.washington.edu, aaron@cs.washington.edu, meltzoff@u.washington.edu

Abstract

Learning through imitation is a powerful and versatile method for acquiring new behaviors. In humans, a wide range of behaviors, from styles of social interaction to tool use, are passed from one generation to another through imitative learning. Although imitation evolved through Darwinian means, it achieves Lamarckian ends: it is a mechanism for the inheritance of acquired characteristics. Unlike trial-and-error-based learning methods such as reinforcement learning, imitation allows rapid learning. The potential for rapid behavior acquisition through demonstration has made imitation learning an increasingly attractive alternative to manually programming robots. In this chapter, we review recent results on how infants learn through imitation and discuss Meltzoff and Moore's four-stage progression of imitative abilities: (i) body babbling, (ii) imitation of body movements, (iii) imitation of actions on objects, and (iv) imitation based on inferring intentions of others. We formalize these four stages within a probabilistic framework for learning and inference. The framework acknowledges the role of internal models in sensorimotor control and draws on recent ideas from the field of machine learning regarding Bayesian inference in graphical models. We highlight two advantages of the probabilistic approach: (1) the development of new algorithms for imitation-based learning in robots acting in noisy and uncertain environments, and (2) the potential for using Bayesian methodologies (such as manipulation of prior probabilities) and robotic technologies to deepen our understanding of imitative learning in humans.

1 Introduction

Humans may aptly be characterized as the most complex, adaptive, and behaviorally flexible of all animals. Evolution has stumbled upon an unlikely but very effective trick for achieving this state. Relative to most other animals, we are born “immature” and helpless. Our extended period of infantile immaturity however confers us with benefits. It allows us to learn and adapt to the specific physical and cultural environment into which we are born. Instead of relying on fixed reflexes adapted for specific environments as in the case of certain animals, our learning capacities allow us to adapt to a wide range of ecological niches, from Alaska to Africa, modifying our shelter, skills, dress, and customs accordingly. A crucial component of evolution's design for human beings is imitation-based learning, the ability to learn behaviors by observing the actions of others.

Human adults effortlessly learn new behaviors from watching others. Parents provide their young with an apprenticeship in how to behave as a member of the culture long before verbal instruction is possible. In western culture, toddlers too young for language hold telephones to their ears and babble into thin air. There is no innate proclivity to treat hunks of plastic in this manner, nor is it due to Skinnerian trial-and-error learning. Imitation is chiefly responsible.

Over the past decade, imitative learning has received considerable attention from cognitive scientists, evolutionary biologists, neuroscientists, and robotics researchers. Discoveries in developmental psychology have altered theories about the origins of imitation and its place in human nature. We used to think that humans gradually learned to imitate over the first several years of life. We now know that newborns can imitate body movements at birth. Such imitation reveals an innate link between observed and executed acts, with important implications for neuroscience. Evolutionary biologists are using imitation in humans and nonhuman animals as a tool for examining continuities and discontinuities in the evolution of mind.

Darwin inquired about imitation in nonhuman animals, but the last 10 years have seen a greater number of controlled studies of imitation in monkeys and great apes than in the previous 100 years. The results indicate that monkey imitation is hard to come by in controlled experiments, belying the common wisdom of "monkey see monkey do" (Tomasello & Call, 1997; Whiten, 2002). Nonhuman primates and other animals (e.g., songbirds) imitate, but their imitative prowess is more restricted than that of humans (Meltzoff, 1996). Meanwhile, neuroscientists and experimental psychologists have started investigating the neural and psychological mechanisms underlying imitation, including the exploration of "mirror neurons" and "shared neural representations" (e.g., Decety, 2002; Prinz, 2002; Meltzoff & Decety, 2003; Rizzolatti, Fadiga, Fogassi, & Gallese, 2002).

The robotics community is becoming increasingly interested in robots that can learn by observing movements of a human or another robot. Such an approach, also called "learning by watching" or "learning by example," promises to revolutionize the way we interact with robots by offering a new, extremely flexible, fast, and easy way of programming robots (Berthouze & Kuniyoshi, 1998; Mataric & Pomplun, 1998; Billard & Dautenhahn, 2000; Breazeal & Scassellati, 2002; Dautenhahn, & Nehaniv, 2002). This effort is also prompting an increased cross-fertilization between the fields of robotics and human psychology (Hayes & Demiris, 1994; Demiris *et al.*, 1997; Schaal, 1999).

In this chapter, we set the stage for re-examining robotic learning by discussing Meltzoff and Moore's theory about how infants learn through imitation (Meltzoff, 2002; Meltzoff & Moore, 1997). They suggest a four stage progression of imitative abilities: (i) body babbling, (ii) imitation of body movements, (iii) imitation of actions on objects, and (iv) imitation based on inferring intentions of others. We formalize these four stages within a probabilistic framework that is inspired by recent ideas from machine learning and statistical inference. In particular, we suggest a Bayesian approach to the imitation learning problem and explore its connections to recently proposed ideas regarding the importance of internal models in sensorimotor control. We conclude by discussing two main advantages of a probabilistic approach: (a) the development of robust algorithms for robotic imitation learning in noisy and uncertain environments, and (b) the potential for applying Bayesian methodologies (such as manipulation of prior probabilities) and robotic technologies to obtain a deeper understanding of imitative learning in human beings. Some of the ideas presented in this chapter appeared in a preliminary form in (Rao & Meltzoff, 2003).

2 Imitative Learning in Human Infants

Experiment results obtained by one of the authors (Meltzoff) and his colleagues over the past two decades suggest a progression of imitative learning abilities in infants, building up from "body babbling" (random experimentation with body movements) in neonates to sophisticated forms of imitation in 18-month-old infants based on inferring the demonstrator's intended goals. We discuss these results below.

2.1 Body Babbling

An important precursor to the ability to learn via imitation is to learn how specific muscle movements achieve various elementary body configurations. This helps the child learn a set of "motor primitives" that could be used as a basis for imitation learning. Experiments suggest that infants do not innately know what muscle movements achieve a particular goal state, such as tongue protrusion, mouth opening, or lip protrusion. It is posited that such movements are learned through an early experiential process involving random trial-and-error learning. Meltzoff and Moore (1997) call this process "body babbling." In body babbling, infants move their limbs and facial parts in repetitive body play analogous to vocal babbling. In the more familiar notion of vocal babbling, the muscle movements are mapped to the resulting auditory consequence; infants are learning an articulatory-auditory relation (Kuhl & Meltzoff, 1996). Body babbling works in the same way, a principal difference being that the process can begin *in utero*. What is acquired through body babbling is a mapping between movements and a resulting body part configuration such as: tongue-to-lips, tongue-between-lips, tongue-beyond-lips. Because both the dynamic patterns of movement and the resulting endstates achieved can be monitored proprioceptively, body babbling can build up a "directory" (an "internal model") mapping movements to goal states. Studies of fetal and neonatal behavior have documented self-generated activity that could serve this hypothesized body babbling function (Patrick *et al.*, 1982). Neonates can acquire a rich store of information through such body babbling. With sufficient practice, they can map out an "act space" enabling new body configurations to be interpolated within this

space. Such an interpretation is consistent with the probabilistic notion of forward models and internal models discussed in Section 3.1.

2.2 Imitating Body Movements

By acquiring the ability to make elementary goal-directed movements through body babbling, even newborn infants demonstrate imitative learning. Meltzoff and Moore (1983, 1989) discovered that newborns can imitate facial acts. The mean age of these infants was 36 hours old, the youngest being 42 minutes old at the time of testing. Facial imitation in human infants thus suggests an innate mapping between observation and execution. Moreover, the studies provide information about the nature of the machinery infants use to connect observation and execution, as will be illustrated in the following brief review.

In Meltzoff & Moore (1977), 12- to 21-day-olds were shown to imitate four different gestures, including facial and manual movements. Infants didn't confuse either actions or body parts. They differentially responded to tongue protrusion with tongue protrusion and not lip protrusion (Figure 1), showing that the specific *body part* can be identified. They also differentially responded to lip protrusion versus lip opening, showing that differential *action patterns* can be imitated with the same body part. This is confirmed by research showing that infants differentially imitate two different kinds of movements with the tongue (Meltzoff & Moore, 1994, 1997). In all, there are more than 24 studies of early imitation from 13 independent laboratories, establishing imitation for an impressive set of elementary body acts (Meltzoff, 2002). This does not deny further development of imitative abilities. Young infants are not as motorically capable as older children and the neonate is certainly less self-conscious about imitating than the toddler (Meltzoff & Moore, 1997). The chief question for theory, however, concerns the neural and psychological processes linking the observation and execution of matching acts. How do infants crack the correspondence problem? Two discoveries bear on this issue.



Figure 1. Imitative responses in 2- to 3-week-old infants (from Meltzoff & Moore, 1977).

First, early imitation is not restricted to direct perceptual-motor resonances. Meltzoff and Moore (1977) put a pacifier in infants' mouths so they couldn't imitate during the demonstration. After the demonstration was complete, the pacifier was withdrawn, and the adult assumed a passive face. The results showed that infants imitated during the subsequent 2.5-minute response period while looking at a passive face. More dramatically, 6-week-olds have been shown to perform deferred imitation across a 24-hour delay (Meltzoff & Moore, 1994). Infants saw a gesture on one day and returned the next day to see the adult with a passive-face pose. Infants stared at the face and then imitated from long-term memory.

Second, infants correct their imitative response (Meltzoff & Moore, 1994, 1997). They converge on the accurate match without feedback from the experimenter. The infant's first response to seeing a facial gesture is activation of the corresponding body part. For example, when infants see tongue protrusion, there is a dampening of movements of other body parts and a stimulation of the tongue. They do not necessarily protrude the tongue at first, but may elevate it or move it slightly in the oral cavity. The important point is that the tongue, rather than the lips or fingers, is energized before the precise imitative movement pattern is isolated. It is as if young infants

isolate what part of their body to move before how to move it. Meltzoff and Moore (1997) call this “organ identification.” Neurophysiological data show that visual displays of parts of the face and hands activate specific brain sites in monkeys and humans (Buccino *et al.*, 2001; Gross, 1992). Specific body parts could be neurally represented at birth and serve as a foundation for infant imitation.

In summary, the results suggest that (a) Newborns imitate facial acts that they have never seen themselves perform, (b) There is an innate observation-execution pathway in humans, and (c) This pathway is mediated by a representational structure that allows infants to defer imitation and to correct their responses without any feedback from the experimenter.

2.3 Imitating Actions on Objects

More sophisticated forms of imitation than facial or manual imitation can be observed in infants who are several months old. In particular, the ability to imitate in these infants begins to encompass actions on *objects* that are external to the infant’s body parts. In one study, toddlers were shown the act of an adult leaning forward and using the forehead to touch a yellow panel (Meltzoff, 1988b). This activated a microswitch, and the panel lit up. Infants were not given a chance for immediate imitation or even a chance to explore the panel during the demonstration session; therefore, learning by reinforcement and shaping was excluded. A 1-week delay was imposed. At that point, infants returned to the laboratory and the panel was put out on the table. The results showed that 67% of the infants imitated the head-touch behavior when they saw the panel. Such novel use of the forehead was exhibited by 0% of the controls who had not seen this act on their first visit. An example of the head-touch response is shown in Figure 2.



Figure 2. A 14-month-old infant imitating the novel action of touching a panel with the forehead (from Meltzoff, 1999).

Successful imitation in this case must be based on observation of the adult’s act because perception of the panel itself did not elicit the target behavior in the naive infants. Moreover, the findings tell us something about what is represented. If the only thing they remembered is that “the panel lit up” (an object property), they would have returned and used their hands to press it. Instead, they re-enacted the same unusual act as used by the adult. The absent act had to have been represented and used to generate the behavior a week later.

The utility of deferred imitation with “real world” objects has also been demonstrated. Researchers have found deferred imitation of peer behavior. In one study, 16-month-olds at a day-care center watched peers play with toys in unique ways. The next day, an adult went to the infants’ house (thereby introducing a change of context) and put the toys on the floor. The results showed that infants played with the toys in the particular ways that they had seen peers play 24 hours earlier (Hanna & Meltzoff, 1993). In another study, 14-month-olds saw a person on television demonstrate target acts with 3-D toys. When they returned to the laboratory the next day, they were handed the toys for the first time. Infants re-enacted the events they saw on TV the previous day (Meltzoff, 1988a). An example is shown in Figure 3.

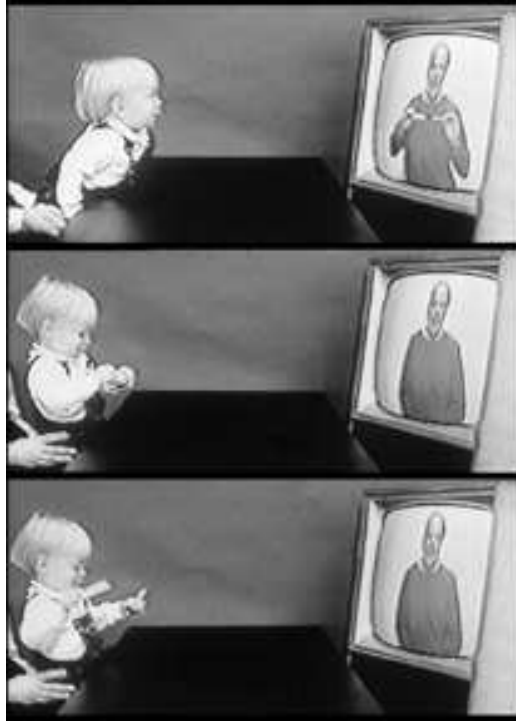


Figure 3. Infants as young as 14 months old imitate actions on objects as seen on TV (from Meltzoff, 1988a).

Taken together, these results indicate that infants who are between 1 to 1.5 years old are adept at imitating not only body movements but also actions on objects such as toys in a variety of contexts. For imitation to be useful in cultural learning, it would have to function with just such flexibility. The ability to imitate the actions of others on external objects undoubtedly played a crucial role in human evolution by facilitating the transfer of knowledge of tool use and other important skills from one generation to the next.

2.4 Inferring Intentions

The most sophisticated forms of imitative learning are those that require an ability to read below the perceived behavior to infer the underlying goals and intentions of the actor. This brings the human infant to the threshold of “theory of mind,” in which they attribute not only visible behaviors to others, but develop the idea that others have internal mental states (intentions, perceptions, emotions) that underlie, predict, and generate these visible behaviors.

One study involved showing 18-month-old infants an unsuccessful act (Meltzoff, 1995). For example, an adult actor “accidentally” under- or overshot his target, or he tried to perform a behavior but his hand slipped several times; thus the goal-state was not achieved (Figure 4, top row). To an adult, it was easy to read the actor’s intention although he did not fulfill it. The experimental question was whether infants also read through the literal body movements to the underlying goal of the act. The measure of how they interpreted the event was what they chose to re-enact. In this case, the correct answer was not to imitate the movement that was actually seen, but the actor’s goal, which remained unfulfilled.

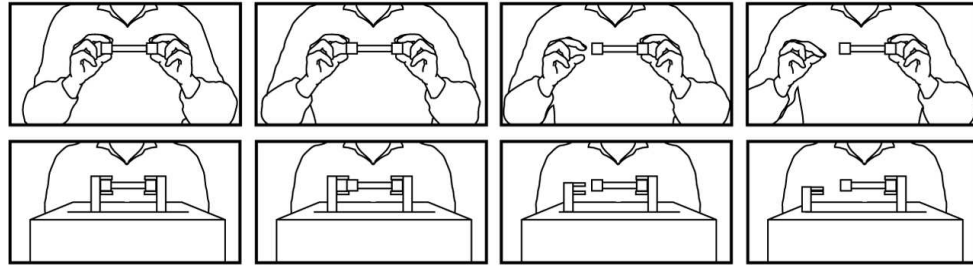


Figure 4. Human actor demonstrating an unsuccessful act (top panel) and an inanimate device mimicking the same movements (bottom). Infants attributed goals and intentions to the human but not to the inanimate device (from Meltzoff, 1995).

The study compared infants' tendency to perform the target act in several situations: (a) after they saw the full target act demonstrated, (b) after they saw the unsuccessful attempt to perform the act, and (c) after it was neither shown nor attempted. The results showed that 18-month-olds can infer the unseen goals implied by unsuccessful attempts. Infants who saw the unsuccessful attempt and infants who saw the full target act both produced target acts at a significantly higher rate than controls. Evidently, toddlers can understand our goals even if we fail to fulfill them.

If infants can pick up the underlying goal or intention of the human act, they should be able to achieve the act using a variety of means. This was tested by Meltzoff (2002) in a study of 18-month-olds using a dumbbell-shaped object that was too big for the infants' hands. The adult grasped the ends of the dumbbell and attempted to yank it apart, but his hands slid off so he was unsuccessful in carrying out his intention. The dumbbell was then presented to the child. Interestingly, the infants did not attempt to imitate the surface behavior of the adult. Instead, they used novel ways to struggle to get the gigantic toy apart. They might put one end of the dumbbell between their knees and use both hands to pull it upwards, or put their hands on inside faces of the cubes and push outwards, and so on. They used *different means* than the demonstrator in order to achieve the *same end*. This fits with Meltzoff's (1995) hypothesis that infants had inferred the goal of the act, differentiating it from the surface behavior that was observed.

People's acts can be goal-directed and intentional but the motions of inanimate devices are not — they are typically understood within the framework of physics, not psychology. In order to begin to assess whether young children distinguish between a psychological versus purely physical framework, Meltzoff (1995) designed an inanimate device made of plastic, metal, and wood. The device had poles for arms and mechanical pincers for hands. It did not look human, but it traced the same spatiotemporal path that the human actor traced and manipulated the object much as the human actor did (see Figure 4). The results showed that infants did not attribute a goal or intention to the movements of the inanimate device. Infants were no more (or less) likely to pull the toy apart after seeing the unsuccessful attempt of the inanimate device as in the baseline condition. This was the case despite the fact that infants pulled the dumbbell apart if the inanimate device successfully completed this act. Evidently, infants can pick up certain information from the inanimate device, but not other information: they can understand successes, but not failures. In the case of the unsuccessful attempts, it is as if they see the motions of the machine's mechanical arms as “physical slippage” but not as an “effort” or “intention” to pull the object apart. They appear to make attributions of intentionality to humans but not to the mechanical device. One goal of our current research program is to examine just how “human” a model must look (and act) in order to evoke this attribution. We plan to test infants' interpretations of the “intentional” acts of robots.

3 A Probabilistic Model of Imitation

In recent years, probabilistic models have provided elegant explanations for a variety of neurobiological phenomena and perceptual illusions (for reviews, see Knill & Richards, 1996; Rao *et al.*, 2002). There is growing evidence that the brain utilizes principles such as probability matching and Bayes theorem for solving a wide range of tasks in sensory processing, sensorimotor control, and decision-making. Bayes theorem in particular has been shown to be especially useful in explaining how the brain combines prior knowledge about a task with current sensory information and how information from different sensory channels are combined based on the noise statistics in these channels (see chapters in Rao *et al.*, 2002).

At the same time, probabilistic approaches are becoming increasingly popular in robotics and in artificial intelligence (AI). Traditional approaches to AI and robotics have been unsuccessful in scaling to noisy and realistic environments due to their inability to store, process, and reason about uncertainties in the real-world. The stochastic nature of most real-world environments makes the ability to handle uncertainties almost indispensable in intelligent autonomous systems. This realization has sparked a tremendous surge of interest in probabilistic methods for inference and learning in AI and robotics in recent years. Powerful new tools known as *graphical models* and *Bayesian networks* (Pearl, 1988) have found wide applicability in areas ranging from data mining and computer vision to bioinformatics and mobile robotics. These networks allow the probabilities of various events and outcomes to be inferred directly from input data based on the laws of probability and a representation based on graphs.

Given the recent success of probabilistic methods in AI/robotics and in modeling the brain, we believe that a probabilistic framework for imitation could not only enhance our understanding of human imitation but also provide new methods for imitative learning in robots. In this section, we explore a formalization of Meltzoff and Moore's stages of imitative learning in infants within the context of a probabilistic model.

3.1 Body Babbling: Learning Internal Models of One's Own Body

Meltzoff and Moore's theory about body babbling can be related to the task of learning an "internal model" of an external physical system (also known as "system identification" in the engineering literature). The physical system could be the infant's own body, a passive physical object such as a book or toy, or an active agent such as an animal or another human. In each of these cases, the underlying goal is to learn a model of the behavior of the system being observed, i.e., to model the "physics" of the system.

A prominent type of internal model is a forward model, which maps actions to consequences of actions. For example, a forward model can be used to predict the next state(s) of an observed system, given its current state and an action to be executed on the system. Thus, if the physical system being modeled is one's own arm, the forward model could be used to predict the sensory (visual, tactile, and proprioceptive) consequences of a motor command to move the arm in a particular direction.

The counterpart of a forward model is an inverse model, which maps desired perceptual states to appropriate actions that achieve those states, given the current state. The inverse model is typically harder to estimate and is often ill-defined, due to many possible actions leading to the same goal state. A more tractable approach, which has received much attention in recent years (Jordan, 1992; Wolpert, 1998), is to estimate the inverse model using a forward model and appropriate constraints on actions (priors), as discussed below.

Our hypothesis is that the progression of imitative stages in infants as discussed in Section 2 reflects a concomitant increase in the sophistication of internal models in infants as they grow older. Intrauterine and early postnatal body babbling could allow an infant to learn an internal model of its own body parts. This internal model is sufficient for the most elementary forms of imitation in Stage 2 involving movement of body parts such as tongue or lip protrusion. Experience with real-world objects after birth allows internal models of the physics of passive objects to be learned, allowing imitation of actions on such objects as seen in Stage 3. By the time infants are about 1.5 years old, they have interacted extensively with other humans, allowing them to acquire internal models (both forward and inverse) of active agents with intentions. Such learned forward models could be used to infer the goals of agents despite witnessing only unsuccessful demonstrations while the inverse models could be used to select the motor commands necessary to achieve the undemonstrated but inferred goals. These ideas are illustrated with a concrete example in a subsequent section.

3.2 Bayesian Imitative Learning

Consider an imitation learning task where the observations can be characterized as a sequence of states s_1, s_2, \dots, s_N of an observed object. A first problem that the imitator has to solve is to estimate these states from the raw perceptual inputs I_1, I_2, \dots, I_N . This can be handled using state estimation techniques such as Kalman or particle filtering. The estimated states would ideally be in object-centered coordinates. The next problem that the imitator has to solve is the correspondence problem (Nehaniv & Dautenhahn, 1998; Alissandrakis *et al.*, 2002): how can the observed states be converted to "my own body states" or states of an object from "my own viewpoint"? Solving the correspondence problem amounts to mapping the estimated object-centered representation to an egocentric representation. In this chapter, for simplicity, we use an identity mapping for this correspondence

function but the methods below also apply to the case of non-trivial correspondences (e.g., (Nehaniv & Dautenhahn, 1998; Alissandrakis *et al.*, 2002)).

In the simplest form of imitation-based learning, the goal is to compute a set of actions that will lead to the goal state s_N , given a set of observed and memorized states s_1, s_2, \dots, s_N . We will treat s_t as the random variable for the state at time t . For the rest of the chapter, we assume discrete state and action spaces. Thus, the state s_t of the observed object could be one of M different states S_1, S_2, \dots, S_M while the current action a_t could be one of A_1, A_2, \dots, A_p .

Consider now a simple imitation learning task where the imitator has observed and memorized a sequence of states (for example, $S_7 \rightarrow S_1 \rightarrow \dots \rightarrow S_{12}$). These states can also be regarded as the sequence of sub-goals that need to be achieved in order to reach the goal state S_{12} . The objective then is to pick the action a_t that will maximize the probability of taking us from a current state $s_t = S_i$ to a memorized next state $s_{t+1} = S_j$, given that the goal state is $s_G = S_k$ (starting from $s_0 = S_7$ for our example). In other words, we would like to select the action A_i that maximizes:

$$P(a_t = A_i | s_t = S_i, s_{t+1} = S_j, s_G = S_k)$$

This set of probabilities constitutes the *inverse model* of the observed system: it tells us what action to choose, given the current state, the desired next state, and the desired goal state.

The action selection problem becomes tractable if a forward model has been learned through body babbling and through experience with objects and agents in the world. The forward model is given by the set of probabilities:

$$P(s_{t+1} = S_j | s_t = S_i, a_t = A_i)$$

Note that the forward model is determined by the environment and is therefore assumed to be independent of the goal state s_G , i.e., $P(s_{t+1} = S_j | s_t = S_i, a_t = A_i, s_G = S_k) = P(s_{t+1} = S_j | s_t = S_i, a_t = A_i)$. These probabilities can be learned through experience in a supervised manner because values for all three variables become known at time step $t+1$. Similarly, a set of prior probabilities on actions $P(a_t = A_i | s_t = S_i, s_G = S_k)$ can also be learned through experience with the world, for example, by tracking the frequencies of each action for each current state and goal state.

Given these two sets of probabilities, it is easy to compute probabilities for the inverse model using Bayes theorem:

$$P(a_t = A_i | s_t = S_i, s_{t+1} = S_j, s_G = S_k) = c P(s_{t+1} = S_j | s_t = S_i, a_t = A_i) P(a_t = A_i | s_t = S_i, s_G = S_k) \quad (1)$$

where $c = 1/P(s_{t+1} = S_j | s_t = S_i, s_G = S_k)$ is the normalization constant that can be computed by marginalizing over the actions:

$$P(s_{t+1} = S_j | s_t = S_i, s_G = S_k) = \sum_m P(s_{t+1} = S_j | s_t = S_i, a_t = A_m) P(a_t = A_m | s_t = S_i, s_G = S_k)$$

Thus, at each time step, an action A_i can either be chosen stochastically according to the probability $P(a_t = A_i | s_t = S_i, s_{t+1} = S_j, s_G = S_k)$ or deterministically as the one that maximizes $P(a_t = A_i | s_t = S_i, s_{t+1} = S_j, s_G = S_k)$. The former action selection strategy is known as probability matching while the latter is known as maximum a posteriori (MAP) selection. In both cases, the probabilities are computed based on the current state, the next sub-goal state, and the final goal state using the learned forward model and priors on actions (Equation 1). This contrasts with reinforcement learning methods where goal states are associated with rewards and the algorithms pick actions that maximize the total expected future reward. Learning the “value function” that estimates the total expected reward for each state typically requires a large number of trials for exploring the state space. In contrast, the imitation-based approach as sketched above utilizes the memorized sequence of sub-goal states to guide the action selection process, thereby significantly reducing the number of trials needed to achieve the goal state. The actual number of trials depends on the fidelity of the learned forward model, which can be fine-tuned during body babbling and “play” with objects as well as during attempts to imitate the teacher.

A final observation is that the probabilistic framework introduced above involving forward and inverse models can also be used to infer the intent of the teacher, i.e., to estimate the probability distribution over the goal states s_G . Note that:

$$\begin{aligned} P(s_G = S_k | a_t = A_i, s_t = S_i, s_{t+1} = S_j) &= k_1 P(s_{t+1} = S_j | s_t = S_i, a_t = A_i, s_G = S_k) P(s_G = S_k | s_t = S_i, a_t = A_i) \\ &= k_2 P(s_{t+1} = S_j | s_t = S_i, a_t = A_i, s_G = S_k) P(a_t = A_i | s_t = S_i, s_G = S_k) P(s_G = S_k | s_t = S_i) \\ &= k_3 P(s_{t+1} = S_j | s_t = S_i, a_t = A_i, s_G = S_k) P(a_t = A_i | s_G = S_k, s_t = S_i) P(s_t = S_i | s_G = S_k) P(s_G = S_k) \end{aligned} \quad (2)$$

where the k_i are normalization constants. The above equations were obtained by repeatedly applying Bayes’ rule. The first probability on the right hand side in Equation (2) is the learned forward model and the second is the

learned prior over actions. The last two probabilities capture the frequency of a state given a goal state and the overall probability of the goal state itself. These would need to be learned from experience during interactions with the teacher and the environment. We illustrate the application of the imitation and inference rules derived above in a simple maze example in the following section.

3.3 Example: Learning to Solve a Maze Task through Imitation

We illustrate the application of the probabilistic approach sketched above to the problem of navigating to specific goal locations within a maze, a classical problem in the field of reinforcement learning. However, rather than learning through rewards delivered at the goal locations (as in reinforcement learning), we illustrate how an “agent” can learn to navigate to specific locations by combining in a Bayesian manner a learned internal model with observed trajectories from a teacher. To make the task more realistic, we assume the presence of noise in the environment leading to uncertainty in the execution of actions.

3.3.1 Learning a Forward Model for the Maze Task

Figure 5 (a) depicts the maze environment consisting of a 20 x 20 grid of squares partitioned into several rooms and corridors by walls, which are depicted as thick black lines. The starting location is indicated by an asterisk (“*”) and the three possible goal locations (Goals 1, 2, and 3) are indicated by circles of different shades. The goal of the imitator is to observe the teacher’s trajectory from the start location to one of the goals and then to select appropriate actions to imitate the teacher.

The states s_t in this example are the grid locations in the maze. The five actions available to the imitator are shown in Figure 5 (b): North (N), East (E), South (S), West (W), or remain in place (X). The noisy “forward dynamics” of the environment for each of these actions is shown in Figure 5 (c) (left panel). The figure depicts the probability of each possible next state s_{t+1} that could result from executing one of the five actions in a given location, assuming that there are no walls surrounding the location. The states s_{t+1} are given relative to the current state i.e., N, E, S, W, or X relative to s_t . The brighter a square, the higher the probability (between 0 and 1), with each row summing to 1. Note that the execution of actions is noisy: when the imitator executes an action, for example $a_t = E$, there is a high probability the imitator will move to the grid location to the east ($s_{t+1} = E$) of the current location but there is also a non-zero probability of ending up in the location west ($s_{t+1} = W$) of the current location. The probabilities in Figure 5 (c) (left panel) were chosen in an arbitrary manner; in a robotic system, these probabilities would be determined by the noise inherent in the hardware of the robot as well as environmental noise. When implementing the model, we assume that the constraints given by the walls are enforced by the environment (i.e. it overrides, when necessary, the states predicted by the forward model in Figure 5 (c)). One could alternately define a location-dependent, global model of forward dynamics but this would result in inordinately large numbers of states for larger maze environments and would not scale well. For the current purposes, we focus on the locally defined forward model described above that is independent of the agent’s current state in the maze.

We examined the ability of the imitator to learn the given forward model through “body babbling” which in this case amounts to “maze wandering.” The imitator randomly executes actions and counts the frequencies of outcomes (the next states s_{t+1}) for each executed action. The resulting learned forward model, obtained by normalizing the frequency counts to yield probabilities, is shown in Figure 5 (c) (right panel). By comparing the learned model with the actual forward model, it is clear that the imitator has succeeded in learning the appropriate probabilities $P(s_{t+1} | s_t, a_t)$ for each value of a_t and s_{t+1} (s_t is any arbitrary location not adjacent to a wall).

3.3.2 Imitation using the Learned Forward Model and Learned Priors

Given a learned forward model, the imitator can use Equation (1) to select appropriate actions to imitate the teacher and reach the goal state. The learned prior model $P(a_t = A_i | s_t = S_i, s_G = S_k)$, which is required by Equation (1), can be learned through experience, for example, during earlier attempts to imitate the teacher or during other goal-directed behaviors. The learned prior model provides estimates of how often a particular action is executed at a particular state, given a fixed goal state. For the maze task, this can be achieved by keeping a count of the number times each action (N, E, S, W, X) is executed at each location, given a fixed goal location.

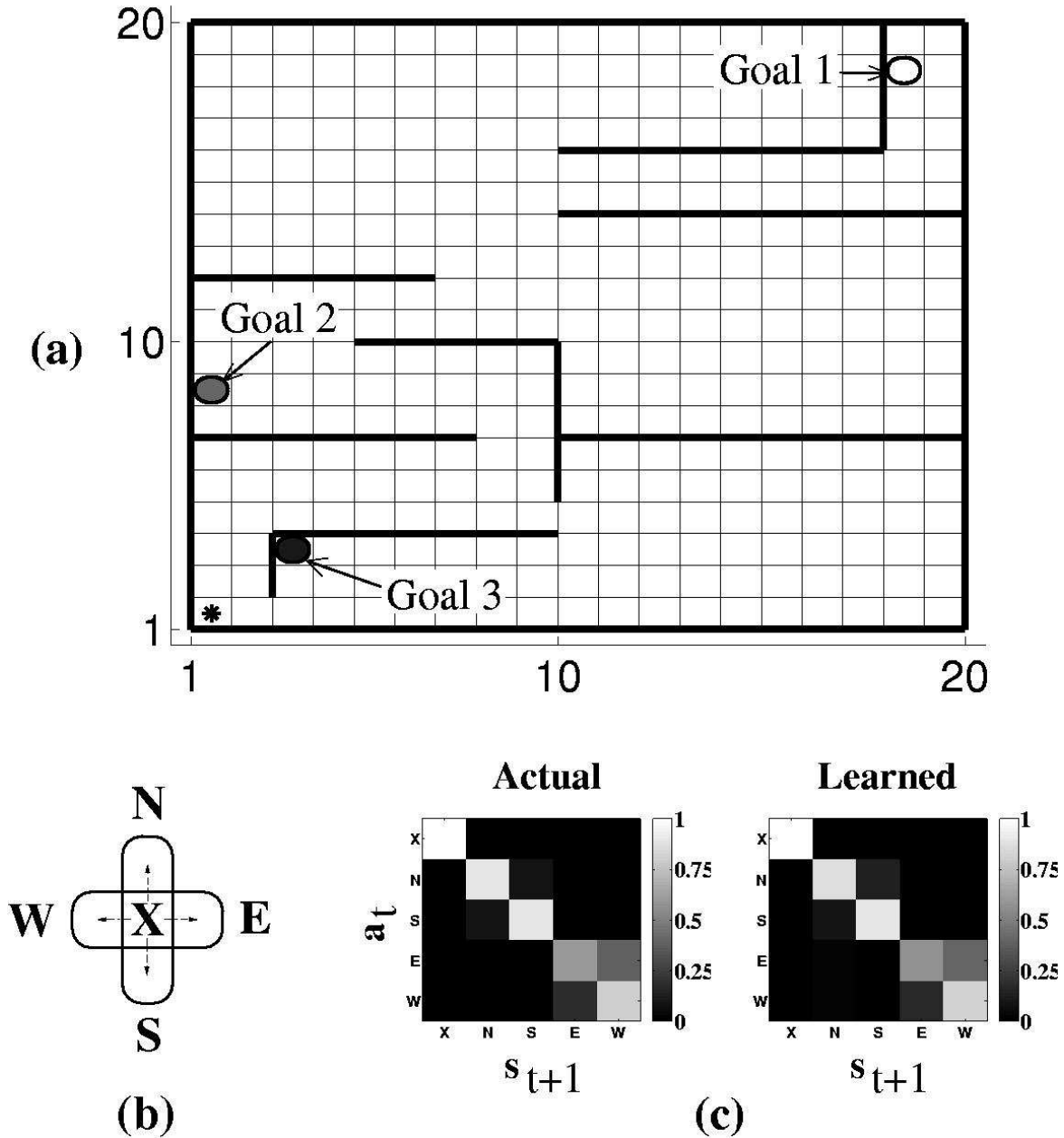


Figure 5. Simulated Maze Environment and Learned Forward Model. (a) Simulated maze environment. Thick lines represent walls. Shaded ovals represent goal states. The instructor and the observer begin each simulated path through the maze at location (1,1), marked by the dark asterisk in the lower left corner of the maze. (b) Five possible actions at a maze location: agents can move north (N), south (S), east (E), west (W), or remain in place (X). (c) Actual and learned probabilistic forward models. The matrix on the left represents the true environmental transition function. The matrix on the right represents an estimated environmental transition function learned through interaction with the environment. Given a current location, each action a_t (rows) indexes a probability distribution over next states s_{t+1} (columns). Note that the learned matrix closely approximates the true transition kernel. These matrices assume the agent is not attempting to move through a wall.

Figure 6 (a) shows the learned prior model $P(a_t = A_i | s_t = S_i, s_G = S_k)$ for an arbitrary location S_i in the maze for four actions $A_i = N, S, E,$ and W when the goal state s_G is the location (1,8) (Goal 2 in Figure 5 (a)). The probability for a given action at any maze location (given Goal 2) is encoded by the brightness of the square in that location in the maze-shaped graph for that action in Figure 6 (a). The probability values across all actions (including X) sum to one for each maze location.

It is clear from Figure 6 (a) that the learned prior distribution over actions given the goal location points in the correct direction for the maze locations near the explored trajectories. For example, for the maze locations along the bottom-left corridor (from (1,5) to (9,5)), the action with the highest probability is E while for locations along the middle corridor (from (1,8) to (9,8)), the action with the highest probability is W . Similar observations hold for sections of the maze where executing N and S will lead the imitator closer the given goal location. The priors for unexplored regions of the maze were set to zero for these simulations (dark regions in Figure 6 (a)).

The learned forward model in Figure 5 (c) can be combined with the learned prior model in Figure 6 (a) to obtain a posterior distribution over actions as specified by Equation (1). Figure 6 (c) shows an example of the trajectory followed by the imitator after observing the two teacher trajectories shown in Figure 6 (b). Due to the noisy forward model as well as limited training data, the imitator needs more steps to reach the goal than does the instructor on either of the training trajectories for this goal, typically involving backtracking over a previous step or remaining in place. Nevertheless, it eventually achieves the goal location as can be seen in Figure 6 (c).

3.3.3 Inferring the Intent of the Teacher

After training, the imitator can attempt to infer the intent of the teacher based on observing some or all of the teacher's actions. Figure 7 (a) depicts an example trajectory of the teacher navigating to the goal location in the top right corner of the maze (Goal 1 in Figure 5 (a)). Based on this observed trajectory of 85 total steps, the task of the imitator in this simple maze environment is to infer the probability distribution over the three possible goal states given the current state, the next state, and the action executed at the current state. The trajectory in Figure 7 (a) was not used to train the observer; instead, this out-of-sample trajectory was used to test the intent inference algorithm described in the text. Note that the desired goal with respect to the prior distributions learned during training is ambiguous at many of the states in this trajectory.

The intent inference algorithm provides an estimate of the distribution over the instructor's possible goals for each time step in the testing trajectory. The evolution of this distribution over time is shown in Figure 7 (b) for the teacher trajectory in (a). Note that the imitator in this case converges to a relatively high value for Goal 1, leading to a high certainty that the teacher intends to go to the goal location in the top right corner. Note also that the probabilities for the other two goals remain non-zero, suggesting that the imitator cannot completely rule out the possibility that the teacher may in fact be navigating to one of these other goal locations. In this graph, the probabilities for these other goals are not very high even at potentially ambiguous locations (such as location (9,9)) because (i) the plotted points represent averages over 5 simulation steps and (ii) Equation (2) depends on $P(s_G = S_k)$, the prior probabilities of goals, which in this case involved higher values for Goal 1 compared to the other goals. Other choices for the prior distribution of goals (such as a uniform distribution) can be expected to lead to higher degrees of ambiguity about the intended goal at different locations. The ability of the imitator to estimate an entire probability distribution over goal states allows it to ascribe degrees of confidence to its inference of the teacher's intent, thereby allowing richer modes of interaction with the teacher than would be possible with purely deterministic methods for inferring intent.

3.3.4 Summary

Although the maze task above is decidedly simplistic, it serves as a useful first example in understanding how the abstract probabilistic framework proposed in this chapter can be used to solve a concrete sensorimotor problem. In addition, the maze problem can be regarded as a simple 2D example of the general sensorimotor task of selecting actions that will take an agent from an initial state to a desired goal state, where the states are typically high-dimensional variables encoding configurations of the body or a physical object rather than a 2D maze location.

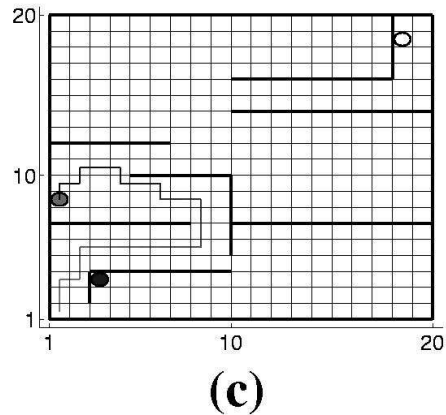
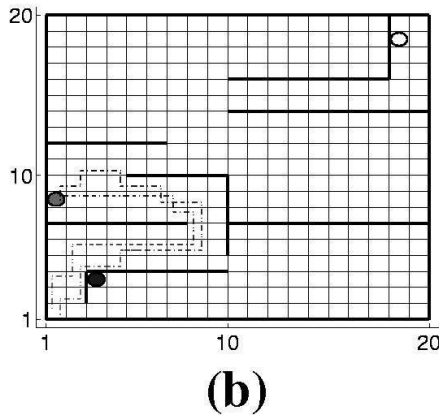
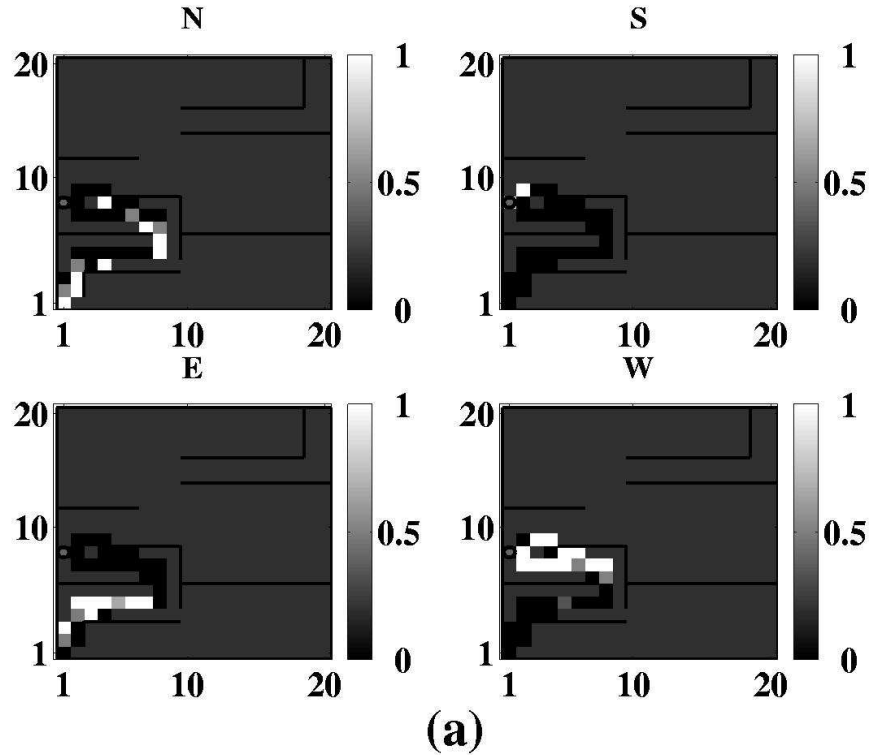


Figure 6. Learned Priors and Example of Successful Imitation: (a) Learned prior distributions $P(a_t | s_t, s_G)$ for the four directional actions (north, south, east, and west) for Goal 2 (map location (1,8)) in our simulated maze environment. Each location in the maze indexes a distribution over actions (the brighter the square, the higher the probability), so that the values across all actions (including X – not shown) sum to one for each maze location. (b) Trajectories (dashed lines) demonstrated by the instructor during training. The goal location here is Goal 2 depicted by the grey circle at map location (1,8). Trajectories are offset within each map cell for clarity; in actuality, the observer perceives the map cell occupied by the instructor at each time step in the trajectory. So, for example, both trajectories start at map cell (1,1). Time is encoded using greyscale values, from light grey (early in each trajectory) to black (late in each trajectory). (c) Example of successful imitation. The observer's trajectory during imitation is shown as a solid line, with greyscale values as in (b). Imitation is performed by combining the learned forward and prior models, as described in the text, to select an action at each step.

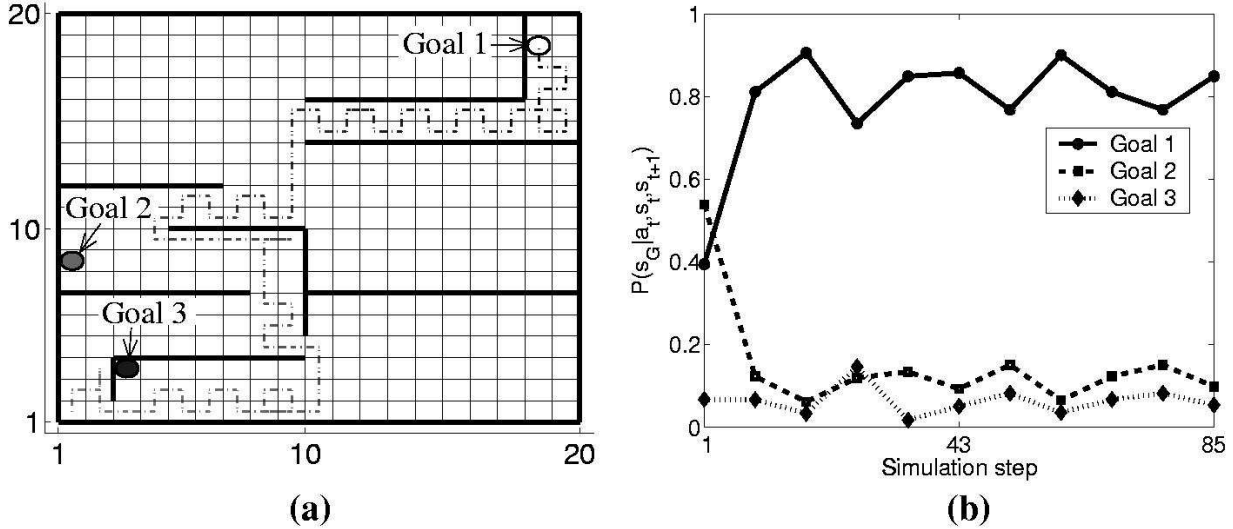


Figure 7. Inferring the intent of the teacher. (a) Dashed line plots a testing trajectory for intent inference. Greyscale values show the progression of time, from light grey (early in the trajectory) to black (late in the trajectory). The intended goal of the instructor was Goal 1 (the white circle at the top right). (b) Inferred intent, shown as a distribution over goal states. Each point in the graph represents the output of the intent inference algorithm, averaged over 8 individual simulation steps (the final data point is an *average* over 5 simulation steps). Note that the instructor's desired goal, goal 1, is correctly inferred as the objective for all points on the graph except the first. Potential ambiguities at different locations are not obvious in this graph due to averaging and unequal priors for the three goals (see text for details).

3.4 Further Applications in Robotic Learning

We are currently investigating the applicability of the probabilistic framework described above to the problem of programming robots through demonstration of actions by human teachers (Demiris *et al.*, 1997; Berthouze & Kuniyoshi, 1998; Mataric & Pomplun, 1998; Schaal, 1999; Billard & Dautenhahn, 2000; Breazeal & Scassellati, 2002; Dautenhahn, & Nehaniv, 2002). Two robotic platforms are being used: a binocular robotic head from Metrica, Inc. (Fig 8 (a)), and a recently acquired Fujitsu HOAP-2 humanoid robot (Fig 8 (b)).

In the case of the robotic head, we have investigated the use of “oculomotor babbling” (random camera movements) to learn the forward model probabilities $P(s_{t+1} = S_j | s_t = S_i, a_t = A_i)$. The states S_i in this case are the feedback from the motors (“proprioception”) and visual information (for example, positions of object features). The learned forward model for the robotic head can be used in the manner described in Section 3.2 to solve head movement imitation tasks (Demiris *et al.*, 1997). In particular, we intend to study the task of robotic gaze following. Gaze following is an important component of language acquisition: to learn words, a first step is to determine what the speaker is looking at, a problem solved by the human infant by about 1 year of age (Brooks & Meltzoff, 2002). We hope to endow robots with a similar capability.

Other work will focus on more complex imitation tasks using the HOAP-2 humanoid robot, which has 25 degrees of freedom, including articulated limbs, hands, and a binocular head (Fig 8 (b)). Using the humanoid, we expect to be able to rigorously test the strengths and weaknesses of our probabilistic models in the context of a battery of tasks modeled after the progressive stages in imitative abilities seen in infants (see Section 2).

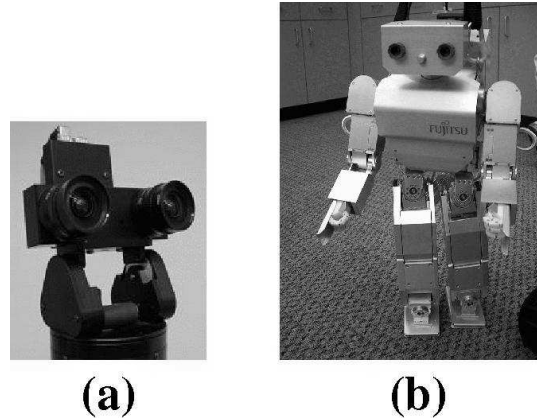


Figure 8. Robotic Platforms for testing Bayesian Imitation Models. (a) A binocular pan-tilt camera platform (“Biclops”) from Metrica, Inc. (b) A miniature humanoid robot (HOAP-2) from Fujitsu Automation, Japan. Both robotic platforms are currently being used to test the Bayesian framework sketched in this chapter.

3.5 Towards a Probabilistic Model for Imitation in Infants

The probabilistic framework sketched above can also be applied to better understand the stages of infant imitation learning described by Meltzoff and Moore. For example, in the case of facial imitation, the states could encode proprioceptive information resulting from facial actions such as tongue protrusion or at a more abstract level, “supramodal” information about facial acts that is not modality-specific (visual, tactile, motor, etc.). Observed facial acts would then be transformed to goal states through a correspondence function, which has been hypothesized to be innate (Meltzoff, 1999). Such an approach is consistent with the proposal of Meltzoff and Moore that early facial imitation is based on active intermodal mapping (AIM) (Meltzoff & Moore, 1977, 1994, 1997). Figure 9 provides a conceptual schematic of the AIM hypothesis. The key claim is that imitation is a matching-to-target process. The active nature of the matching process is captured by the proprioceptive feedback loop. The loop allows infants’ motor performance to be evaluated against the seen target and serves as a basis for correction. One implementation of such a match-and-correction process is the Bayesian action selection method described above with both visual and proprioceptive information being converted to supramodal states.

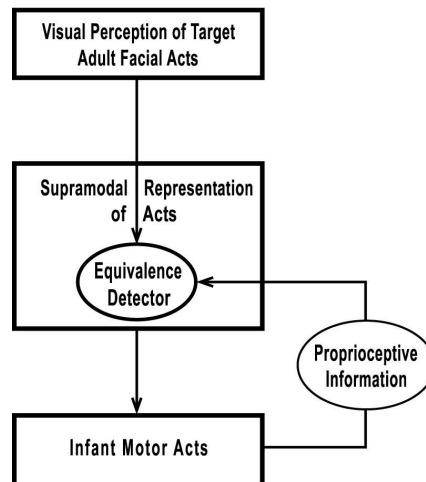


Figure 9. Meltzoff and Moore’s AIM model of facial imitation (from Meltzoff & Moore, 1997).

As a second example of the application of the probabilistic framework, consider imitation learning of actions of objects. In this case, the states to be encoded are the states of the object (“joined together,” “pulled apart,” etc. for the dumbbell-shaped object mentioned above). The forward model to be used would presumably be one that has been learned from experience with similar objects (“objects that can be pulled apart”). This, along with the learned priors for various actions, would allow appropriate actions to be selected based on the observed sequence of object states.

Finally, consider the case where an infant learns from unsuccessful demonstrations by inferring the intention of a human demonstrator. In this case, forward models could be put to good use to infer intention. By using a forward model of a human manipulating an object, the consequences of attempted actions by the human demonstrator can be predicted. For example, in the case of the dumbbell-shaped object used by Meltzoff (1995), the learned forward model would predict that when a person is applying forces at the two ends in opposite directions (away from the center), there is a high probability for the state where the object has been “pulled apart” into two halves. This state could in turn be adopted as the desired goal state and the appropriate action that maximizes the probability of achieving this state could be selected in the Bayesian manner described above.

4 Prospects for a Developmental Robotics

Humans at birth do not have the full set of skills and behaviors exhibited by adults. Human beings are not “turn key” systems that function perfectly out of the box. There are at least four sources of behavioral change in human development: (a) maturational changes in the sensory, motor, and cognitive system, (b) reinforcement learning, (c) independent invention and discovery, often called “insight,” and (d) imitative learning. The first three have been widely celebrated: maturation is discussed by neuroscientists; reinforcement learning by Skinner and generations of learning theorists; and independent invention and solitary discovery by Piaget and others. The imitative competence of young infants has only recently been discovered, and its enormous impact on human development and learning only recently sketched (Meltzoff, 2002). Imitative learning is more flexible and responsive to cultural norms than maturation; it is safer for the child than Skinnerian trial-and-error learning; and it is faster than relying on Piagetian solitary discoveries. These advantages of imitation learning apply equally well to robots and other autonomous agents. In particular, learning through imitation offers substantial benefits over other leading robotic learning methods (such as reinforcement learning) by (1) overcoming the need for a huge number of learning trials and (2) avoiding the need for risky and dangerous experimentation during learning. At the same time, unlike supervised learning methods, imitative learning does not require a human to program the exact motor signals needed to accomplish each task – the robot deduces these based only on observing a human or robotic demonstrator.

In this chapter, we discussed some of the main results obtained from studies of imitation-based learning in infants. These results suggest a four stage progression of imitative learning abilities: (i) body babbling, (ii) imitation of body movements, (iii) imitation of actions on objects, and (iv) imitation based on inferring intentions of others. We formalized these stages within a probabilistic framework inspired by recent ideas from machine learning and provided an example demonstrating the application of Bayesian ideas to the imitation learning problem.

The probabilistic approach is well-suited to imitation learning in real-world robotic environments which are noisy and uncertain. The success of recent approaches to robotic navigation and control can be attributed to the use of probabilistic techniques such as Kalman filtering and particle filtering for handling uncertainty (Blake, 1992; Fox *et al.*, 2000). Similarly, techniques based on statistical learning form the backbone of several recent successful computer vision systems for tracking and recognizing persons (for example, see Jojic & Frey, 2001). We are optimistic that a probabilistic approach to robotic imitation learning will offer many of the advantages of these preceding systems, including the ability to handle missing data, robustness to noise, ability to make predictions based on learned models, etc. We are currently testing our ideas on a binocular robotic head and a humanoid robot.

The probabilistic approach also opens up the possibility of applying Bayesian methodologies such as manipulation of prior probabilities of task alternatives to obtain a deeper understanding of imitation in humans. Such manipulations have yielded valuable information regarding the type of priors and internal models that the adult human brain uses in perception (see chapters in (Rao *et al.*, 2002)) and in motor learning (Wolpert *et al.*, 1995). We believe that the application of such methodology to imitation could shed new light on the problem of how infants acquire internal models of the people and things they encounter in the world. Conversely, we believe that biologically-inspired models will help shape the architecture and algorithms used to solve imitation-based learning problems in robots (cf. (Demiris *et al.*, 1997; Hayes & Demiris, 1994; Schaal, 1999)). For example, Meltzoff and Moore's four stages of imitation in infants suggests a hierarchical approach to robotic imitation, starting from learning internal models of self motion to more sophisticated models of interactions with active behaving agents.

Imitation is an especially fruitful domain for interdisciplinary collaboration between robotics and developmental science. It is a perceptual-motor activity of great adaptive value and a channel for learning that lends itself to

computational modeling. Additionally, it presents an interesting challenge to robotics and offers an extremely versatile and flexible way to program robots. Such interdisciplinary collaborations could eventually allow us to investigate interactions between young children and robots. Do young children — prior to developing the prejudices and philosophies of adults — think that robots have subjective beliefs, desires, emotions, and intentions? Experiments addressing such questions will not only provide new insights into how humans develop a “theory of other minds,” but at the same time, will allow us to use unprejudiced humans (children) as judges of robots in a new form of the celebrated “Turing test” for autonomous machines. We therefore look forward to rich bi-directional benefits emerging from collaborations between developmental science and robotics in the coming years.

Acknowledgments

This work is supported by grants to RPNR from ONR (grant no. N00014-03-1-0457) and the Packard Foundation, and a grant from NIH (HD-22514) to ANM.

References

- Alissandrakis, A., Nehaniv, C. L., & Dautenhahn, K. (2002). Do as I do: correspondences across different robotic embodiments. In D. Polani, J. Kim, and T. Martinez, editors, *Proc. Fifth German Workshop on Artificial Life*, pages 143-152, 2002.
- Berthouze, L., & Kuniyoshi, Y. (1998). Emergence and categorization of coordinated visual behavior through embodied interaction. *Machine Learning*, *31*, 187-200.
- Billard, A., & Dautenhahn, K. (2000). Experiments in social robotics- Grounding and use of communication in robotic agents. *Adaptive Behavior*, *7*, 3-4.
- Blake, A. & Yuille, A. (Eds.). *Active Vision*. MIT Press, Cambridge, MA, 1992.
- Breazeal, C., & Scassellati, B. (2002). Challenges in building robots that imitate people. In K. Dautenhahn & C. L. Nehaniv (Eds.), *Imitation in animals and artifacts* (pp. 363-390). Cambridge, MA: MIT Press.
- Brooks, R., & Meltzoff, A. N. (2002). The importance of eyes: How infants interpret adult looking behavior. *Developmental Psychology*, *38*, 958-966.
- Buccino, G., Binkofski, F., Fink, G. R., Fadiga, L., Fogassi, L., Gallese, V., Seitz, R. J., Zilles, K., Rizzolatti, G., & Freund, H.-J. (2001). Action observation activates premotor and parietal areas in a somatotopic manner: an fMRI study. *European Journal of Neuroscience*, *13*, 400-404.
- Dautenhahn, K., & Nehaniv, C. (2002). *Imitation in animals and artifacts*. Cambridge, MA: MIT Press.
- Decety, J. (2002). Is there such a thing as functional equivalence between imagined, observed, and executed action? In A. N. Meltzoff & W. Prinz (Eds.), *The imitative mind: Development, evolution, and brain bases* (pp. 291-310). Cambridge: Cambridge University Press.
- Demiris, J., Rougeaux, S., Hayes, G. M., Berthouze, L., & Kuniyoshi, Y. (1997). Deferred imitation of human head movements by an active stereo vision head. *Proceedings of the 6th IEEE International Workshop on Robot and Human Communication* (Sept. 29-Oct. 1, Sendai, Japan).
- Fox, D., Thrun, S., Dellaert, F., & Burgard, W. Particle filters for mobile robot localization. In A. Doucet, N. de Freitas, and N. Gordon (eds.), *Sequential Monte Carlo Methods in Practice*. Springer Verlag, New York, 2000.

- Gross, C. G. (1992). Representation of visual stimuli in inferior temporal cortex. In V. Bruce, A. Cowey, & A. W. Ellis (Eds.), *Processing the facial image* (pp. 3-10). New York: Oxford University Press.
- Hanna, E., & Meltzoff, A. N. (1993). Peer imitation by toddlers in laboratory, home, and day-care contexts: Implications for social learning and memory. *Developmental Psychology*, *29*, 701-710.
- Hayes, G., & Demiris, J. (1994). A robot controller using learning by imitation. *Symposium conducted at the International Symposium on Intelligent Robotic Systems*, Grenoble, France.
- Jojic, N. & Frey, B. Learning flexible sprites in video layers. *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2001.
- Jordan, M. I. & Rumelhart, D. E. (1992). Forward models: Supervised learning with a distal teacher. *Cognitive Science*, *16*, 307-354.
- Knill, D. C. & Richards, W. (Eds.) (1996). *Perception as Bayesian Inference*. Cambridge, UK: Cambridge University Press.
- Kuhl, P. K., & Meltzoff, A. N. (1996). Infant vocalizations in response to speech: Vocal imitation and developmental change. *Journal of the Acoustical Society of America*, *100*, 2425-2438.
- Mataric, M. J., & Pomplun, M. (1998). Fixation behavior in observation and imitation of human movement. *Cognitive Brain Research*, *7*, 191-202.
- Meltzoff, A. N. (1988a). Imitation of televised models by infants. *Child Development*, *59*, 1221-1229.
- Meltzoff, A. N. (1988b). Infant imitation after a 1-week delay: Long-term memory for novel acts and multiple stimuli. *Developmental Psychology*, *24*, 470-476.
- Meltzoff, A. N. (1988c). The human infant as *Homo imitans*. In T. R. Zentall & B. G. Galef (Eds.), *Social learning: Psychological and biological perspectives* (pp. 319-341). Hillsdale, NJ: Erlbaum.
- Meltzoff, A. N. (1996). The human infant as imitative generalist: A 20-year progress report on infant imitation with implications for comparative psychology. In C. M. Heyes & B. G. Galef (Eds.), *Social learning in animals: The roots of culture* (347-370). NY: Academic Press.
- Meltzoff, A. N. (1999). Origins of theory of mind, cognition, and communication. *Journal of Communication Disorders*, *32*, 251-269.
- Meltzoff, A. N. (2002). Elements of a developmental theory of imitation. In A. N. Meltzoff & W. Prinz (Eds.), *The imitative mind: Development, evolution, and brain bases* (pp. 19-41). Cambridge: Cambridge University Press.
- Meltzoff, A. N., & Moore, M. K. (1977). Imitation of facial and manual gestures by human neonates. *Science*, *198*, 75-78.
- Meltzoff, A. N., & Moore, M. K. (1983). Newborn infants imitate adult facial gestures. *Child Development*, *54*, 702-709.
- Meltzoff, A. N., & Moore, M. K. (1989). Imitation in newborn infants: Exploring the range of gestures imitated and the underlying mechanisms. *Developmental Psychology*, *25*, 954-962.
- Meltzoff, A. N., & Moore, M. K. (1994). Imitation, memory, and the representation of persons. *Infant Behavior and Development*, *17*, 83-99.

- Meltzoff, A. N., & Moore, M. K. (1997). Explaining facial imitation: A theoretical model. Early Development and Parenting, 6, 179-192.
- Meltzoff, A. N. (1995). Understanding the intentions of others: Re-enactment of intended acts by 18-month-old children. Developmental Psychology, 31, 838-850.
- Meltzoff, A. N., & Decety, J. (2003). What imitation tells us about social cognition: A rapprochement between developmental psychology and cognitive neuroscience. Philosophical Transactions of the Royal Society B, 358, 491-500.
- Nehaniv, C. & Dautenhahn, K. (1998). Mapping between dissimilar bodies: affordances and the algebraic foundations of imitation. In J. Demiris and A. Birk, editors, *Proc. European Workshop on Learning Robots*.
- Patrick, J., Campbell, K., Carmichael, L., Natale, R., & Richardson, B. (1982). Patterns of gross fetal body movement over 24-hour observation intervals during the last 10 weeks of pregnancy. American Journal of Obstetrics and Gynecology, 142, 363-371.
- Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems*. San Mateo CA: Morgan Kaufman.
- Prinz, W. (2002). Experimental approaches to imitation. In A. N. Meltzoff & W. Prinz (Eds.), *The imitative mind: Development, evolution, and brain bases* (pp. 143-162). Cambridge: Cambridge University Press.
- Rao, R. P. N. & Meltzoff, A. N. (2003). Imitation learning in infants and robots: Towards probabilistic computational models. *Proceedings of the 2003 Artificial Intelligence and Simulation of Behavior (AISB) Convention: Cognition in Machines and Animals*, UK, 2003.
- Rao, R. P. N., Olshausen, B. A. & Lewicki, M. S. (Eds.) (2002). *Probabilistic Models of the Brain: Perception and Neural Function*. Cambridge, MA: MIT Press.
- Rizzolatti, G., Fadiga, L., Fogassi, L., & Gallese, V. (2002). From mirror neurons to imitation, facts, and speculations. In A. N. Meltzoff & W. Prinz (Eds.), *The imitative mind: Development, evolution, and brain bases* (pp. 247-266). Cambridge: Cambridge University Press.
- Schaal, S. (1999). Is imitation learning the route to humanoid robots? Trends in Cognitive Sciences, 3, 233-242.
- Tomasello, M., & Call, J. (1997). *Primate Cognition*. New York: Oxford University Press.
- Whiten, A. (2002). The imitator's representation of the imitated: Ape and child. In A. N. Meltzoff & W. Prinz (Eds.), *The imitative mind: Development, evolution, and brain bases* (pp. 98-121). Cambridge: Cambridge University Press.
- Wolpert, D. M., Ghahramani, Z. & Jordan, M. I. (1995). An internal model for sensorimotor integration. Science 269, 1880-1882.
- Wolpert, D. M. & Kawato, M. (1998). Multiple paired forward and inverse models for motor control, Neural Networks 11(7-8): 1317-1329.