Effects of Social Exploration Mechanisms on Robot Learning

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***Abstract*— Social learning in robotics has largely focused on imitation learning. Here we take a broader view and are interested in the multifaceted ways that a social partner can influence the learning process. We implement four social learning mechanisms on a robot: *stimulus enhancement*, *emulation*, *mimicking*, and *imitation*, and illustrate the computational benefits of each. In particular, we illustrate that some strategies are about directing the attention of the learner to objects and others are about actions. Taken together these strategies form a rich repertoire allowing social learners to use a social partner to greatly impact their learning process. We demonstrate these results in simulation and with physical robot 'playmates'.**

I. Introduction

Social partners can guide a learning process by directing the learner's attention to informative parts of the environment or by suggesting informative actions for the learner. Humans and some animals are equipped with various mechanisms that take advantage of social partners. Understanding these mechanisms and their role in learning will be useful in building robots with similar abilities to benefit from other agents (humans or robots) in their environment, and explicit teaching attempts by these agents.

We are motivated by four social learning mechanisms identified in biological systems [Tomasello, 2001], [Call and Carpenter, 2002]:

- *Stimulus (local) enhancement* is a mechanism through which an observer (child, novice) is drawn to objects others interact with. This facilitates learning by focusing the observer's exploration on interesting objects–ones useful to other social group members.
- *Emulation* is a process where the observer witnesses someone produce a goal or particular result on an object, but then employs its own action repertoire to produce the result. Learning is facilitated both by attention direction to an object of interest and by observing the goal.
- *Mimicking* corresponds to the observer copying the actions of others without an appreciation of their purpose. The observer later comes to discover the effects of the action in various situations. Mimicking suggests, to the observer, actions that can produce useful results.
- *Imitation* refers to reproducing the actions of others to obtain the same results with the same goal.

Robotics research has often focused on the last and most complex of these four mechanisms–imitation; working towards robots capable of reproducing demonstrated motor actions [Shaal, 2002], learning generalized task representations [Pardowitz and Dillmann, 2007], policies [Chernova and Veloso, 2007] or a proto-language about actions [Billard, 2002]. A body of research is devoted to finding ways to learn the imitative behavior itself [Nehaniv and Dautenhahn, 2002], [Demiris and Hayes, 2002]. Some focus on task- or goal-level imitation, reproducing the task not through imitative behavior, but with the robot's own actions [Kuniyoshi et al., 1994], [Montesano et al., 2008], [Jansen, 2005]. This resembles emulation. Other work focuses on adjusting a robot's *actions* while imitating a human demonstration. This can involve extracting trajectory representations in joint and task space [Calinon and Billard, 2008], dynamical equations to control the robot's movements [Pastor et al., 2009] or a sequence of primitive actions [Amit and Mataric, 2002].

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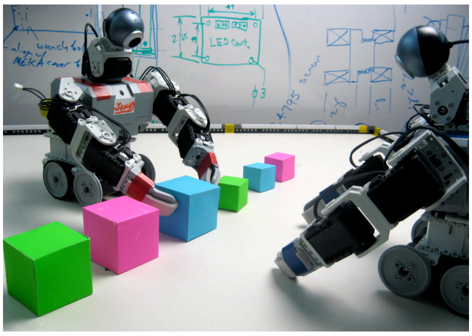


Fig. 1. Robot playmates Jimmy and Jenny in the playground.

As in previous work [Cakmak et al., 2009], we are interested in the variety of ways that a social partner influences learning. In this paper we analyze the impact of *stimulus enhancement*, *emulation*, *mimicking* and *imitation*, articulating the distinct computational benefits of each mechanism.

We show that all four social strategies provide learning benefits over self exploration, particularly when the target goal of learning is a rare occurrence in the environment. We characterize differences between the four strategies, showing that the best strategy depends on both the nature of the problem space and the current behavior of the social partner.

II. Approach

In this work, we have a social learning situation composed of two robot playmates with similar action and perception capabilities. Our experiments focus on learning the sound-making affordance for different objects in the environment.

A. Robot Platform

Jimmy and Jenny (Fig. 1) are upper torso humanoids on wheels built from Bioloid kits and Webcams. Their 8 degrees of freedom enable arm movements, torso rotation and neck tilt. The wheels are used to navigate the workspace.

The behavior system is implemented in C6, a branch of the latest revision of the *Creatures* architecture for interactive characters [Blumberg et al., 2002]. This controls the real robots with percepts from sensors, as well as a simulated version of the robots with virtual sensors and objects.

The behavior system implements a finite state machine to control the exploration for collecting experiences. In individual exploration the robot (i) observes the environment, (ii) approaches the most salient object, (iii) performs the selected action, (iv) observes the outcome (sound or no sound), (v) goes back to its initial position and (vi) updates the saliency of objects and actions based on its exploration strategy. In social exploration, after each object interaction the robot goes into an *observing* state and performs the same updates, of object saliency and action desirability, based on its observation of the other agent's interaction. Observation is based on perception and network communication.

B. Learning Task

Our experiments focus on the task of *affordance learning*–learning a relation between a *context* in which an *action* produces a certain *outcome*. This is learned from interaction experiences consisting of `context-action-outcome` tuples [Sahin et al., 2007]. We use a 2-class Support Vector Machine (SVM) classifier[1] to predict an action's effect in a given environmental context. The SVM inputs are the perceived features of the interacted object and the parameters of the action performed on that object. The prediction target is whether or not this `context-action` produces sound. In this framework the robot is simultaneously learning the object features and action parameters required to produce a desired effect in the environment.

Our goal is to compare social and individual *exploration strategies*, *i.e.* rules for interacting with the environment to collect experience tuples. For robot learning, the social learning mechanisms are ways of guiding the robot's exploration of the space. While stimulus enhancement and emulation direct the learner's attention to informative parts of the *object space* [Cakmak et al., 2009], *mimicking* guides the learner in the *action space*. *Imitation* combines the benefits of both types of strategies. The alternative to social learning is individual learning, in which a robot can use various exploration strategies.

An exploration strategy is implemented as an attention mechanism, where each object attribute and action parameter has a corresponding saliency. The robot always performs the most salient action on the most salient object. Each strategy has a different rule for updating saliencies after every interaction. While individual exploration can take into account past experiences, social exploration can also benefit from observed interactions of the other robot.

[1]The choice of classifier is not crucial for the results of this study. SVMs are widely used discriminative classifiers.

C. Objects

The learning environment involves objects with three discrete perceived attributes: *color*, *size* and *shape*, and one hidden property of *sound-maker*. Different environments are composed of objects with different combinations of these properties. For instance, all green objects could be sound makers in one environment, while in another all objects with a particular shape and size are sound-makers.

Based on prior work [Thomaz and Cakmak, 2009], we hypothesize that social learning will be especially beneficial in the case of rare sound-makers; thus, we systematically vary the frequency of sound-makers in the environment to compare various individual and social exploration strategies.

The simulation environment has 24 objects with different attributes (one of 4 colors, 3 sizes and 2 shapes). We control the percentage of objects in the environment that produce sound, resulting in six learning environments with 75%, 50%, 25%, 17%, 8%, and 4% sound-makers. The physical experiments have 4 objects (2 colors, 2 sizes), in one of two learning environments where (i) all small objects make sound (50%) and (ii) only one object makes sound (25%).

D. Actions

The playmates' action set has two actions: *poke*–a single arm swing (*e.g.*, for pushing objects) and *grasp*–a coordinated swing of both arms. Both involve an initial *approach* to an object of interest, and are parametrized with the following discrete parameters (i) acting distances and (ii) grasp width or (iii) poking speed. In simulation we use 24 different actions (poke or grasp, 3 grasp widths, 3 poke speeds and 3 acting distances). On the physical robots there are 18 possible actions (3 action parameters per distance).

As with objects, we vary the frequency of sound-producing interactions by tuning the actions to have different effects on the objects, yielding different learning problems (i.e., sound-making rareness); for example, by making only one or both of the actions able produce sound and by varying the range of grasp width, poking speed and acting distance within which an action produces sound.

In the simulation experiments, we have six cases in which 75%, 50%, 25%, 17%, 8%, and 4% of the action set are able to produce sound when executed on a sound-maker object. In the physical experiment we consider only two cases in which (i) poke always produces a sound (50%) and (ii) only one particular set of parameters for the grasp produces a sound and poke does not produce a sound (3%).

III. Experiments

We conducted a series of experiments, each collects one data set of experience which is then used to train a sound-maker SVM classifier. In each experiment the learner uses a particular exploration strategy, given an environmental context (object/action sound-maker frequency), and the social partner has a pre-defined behavior. This section describes the exploration strategies and social partner behaviors.

A. Individual Learning

As a baseline for comparison with social learning, three individual exploration strategies are implemented.

1) Random: In each interaction, the saliency of each object attribute and action parameter is randomized, and the robot selects the most salient object and action.

2) Goal-directed: In this strategy, the robot interacts with objects similar to ones that have given the desired effect previously using actions similar to those that previously produced sound. If an interaction produces sound, the saliency of attributes and action parameters used in that interaction are increased and the saliency of others are decreased. When there is no sound, the random strategy is used.

3) Novelty-based: The third strategy is based on a preference for novel objects and actions. After every interaction the saliency of attributes of the object that was interacted with is decreased, while the saliency of different attributes is increased. Actions and action parameters are altered similarly.

B. Social Learning

We implement four social exploration strategies.

1) Stimulus Enhancement: The robot prefers to interact with objects that its playmate has interacted with. After every observed interaction, the learner increases the saliency of attributes of the object that the social partner has interacted with and decreases others.

2) Emulation: The robot prefers objects seen to have given the desired effect. If an observed interaction produces sound, the saliencies of the attributes of the object used are increased. Otherwise, the saliencies are randomly increased or decreased.

3) Mimicking: This strategy involves copying the actions of the social partner. We implement two versions:

- *Blind*: The learner mimics every action of its partner.
- *Goal-based*: The learner mimics actions only after it observes the goal.

Use of the term 'mimicking' in animal behavior literature is closer to *blind*, but this distinction is useful in illustrating computational differences between the social mechanisms.

4) Imitation: In imitation, the learner focuses on the objects used by its social partner and copies the actions of the social partner. Again, there are two versions:

- *Blind*: The learner always imitates its social partner.
- *Goal-based*: It imitates after it observes the goal.

Both stimulus enhancement and emulation influence object attribute saliencies, but do not imply anything about actions. Action selection is random in these strategies. On the other hand, mimicking influences action saliencies while having no implication on objects. Object saliencies are updated randomly in mimicking. Imitation combines the strength of both, varying both the object and action saliencies based on the observation of the social partner. The implementation of the mechanisms and their use of object, action and result components of the demonstration are summarized in Fig. 2.

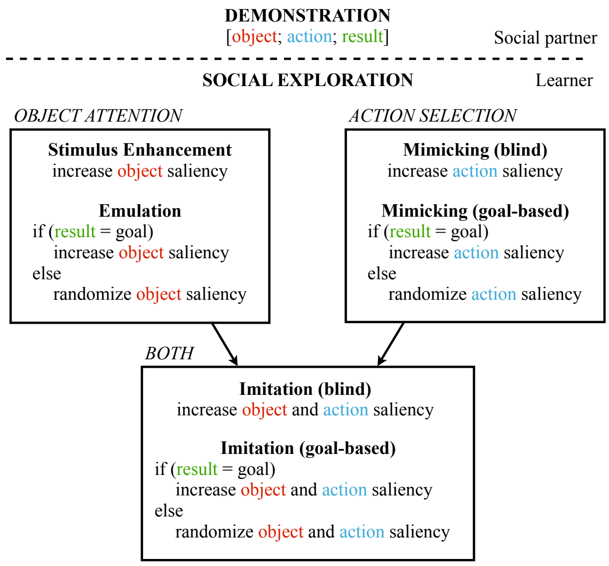


Fig. 2. Implementation of the social learning mechanisms and their use of object, action and result information from the social partner's demonstration.

C. Social Partner Behavior

The behavior of the social partner has a crucial effect on the learner. With particular social partner behaviors, these strategies can become equivalent. For instance if the partner produces a sound with every interaction, stimulus enhancement and emulation behave very similarly. If the partner explores objects and actions randomly, a learner that blindly imitates will learn as if it was exploring randomly itself. Therefore to compare the strategies fairly, we systematically vary the behavior of the social partner.

There are four possible types of demonstrations in terms of the useful information communicated to the learner:

- *Goal-demonstration*: The learner's target goal (sound) is shown with an appropriate action (a sound-producing action) and appropriate object (a sound-maker object).
- *Action-demonstration*: A sound-producing action is demonstrated on a non-sound-maker object.
- *Object-demonstration*: A non-sound-producing action is performed on a sound-maker object.
- *Negative-demonstration*: A non-sound-producing action is performed on a non-sound-maker object.

Social partner behaviors emerge as a result of different demonstration preferences. We consider three behaviors, summarized in Table I:

a) Social partner with same goal: In this case, the goal of the social partner largely overlaps with that of the learner. The partner spends a lot of time demonstrating the goal.

b) Social partner with different goal: Here, the goal of the partner has a small overlap with the learner and it spends little time demonstrating the goal.

c) Social partner with focused demonstration: In the third case the partner spends most of its time focusing either on the target action or object, without producing the goal.

TABLE I

DEMONSTRATION TYPE PREFERENCES FOR THREE SOCIAL PARTNER BEHAVIORS.

Demo. Type	Same-goal	Different-goal	Focused-demo.
Goal-demo.	60%	20%	20%
Action-demo.	20%	20%	80/0%
Object-demo.	20%	20%	0/80%
Neg.-demo.	0%	40%	0%

IV. RESULTS

We first present results from simulation for all environments, exploration strategies and social partner behaviors. Different environments have different frequencies of sound producing interactions. We first keep the percentage of sound producing actions constant at 25% and vary the sound-maker object rareness; and then keep the object percentage constant at 25% and vary the percentage of sound producing actions. We compare all of the individual and social exploration strategies described in Sec. III-A and III-B with each social partner behavior described in Sec. III-C. Then we present results from the physical robots in a simplified environment.

Our performance measure is recall rate[2] in prediction of the effect for all `object-action` combinations. This involves 576 (24x24) test cases in simulation and 72 (4x18) test cases in the physical experiment. The classifiers are trained in a batch mode after 28 interactions in simulation and 8 interactions in the physical robot experiment. These numbers correspond to a small subset of all possible interactions (5% and 10% respectively for simulation and physical experiments). The experiments are repeated 200 times in simulation and 5 times on the physical robots with random initialization for each environment. We report average performance across these experiments.

Fig. 3 gives a comparison of individual and social learning mechanisms in environments with different sound-maker frequencies (the social partner for the social learning strategies has the *same goal*). Performance of social learning with a *same goal* social partner is presented again in Fig. 4 for environments with different sound-maker object frequencies and different sound producing action frequencies. Similarly, performance for learning with a *different goal* social partner is given in Fig. 5; and for learning with a *focused demonstrations* social partner is given in Fig. 6. In this section, we analyze these results with respect to the environments in which each strategy is preferable. The effect of sound-maker rareness on learning performance, as determined by one-way ANOVA tests, are reported on each graph. Additionally, the significance level of the difference between the two strategies plotted in each graph according to a T-test are indicated (* for $p < .05$, ** for $p < .005$). The T-tests indicate the difference between the blind and goal-directed versions of the strategies that focus on a particular aspect of the learning space (object space, action space or both).

[2]Recall corresponds to the ratio of true positives and the sum of true positives and false negatives. Due to space limitations, in this paper we restrict our analysis to effects on recall rate.

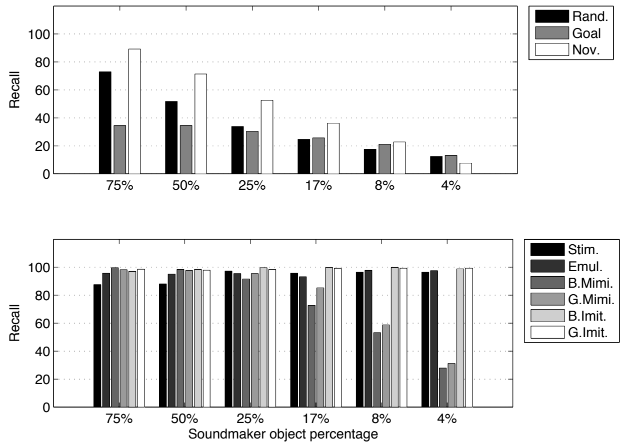


Fig. 3. Comparison of individual and social learning mechanisms for different sound-maker object frequencies. The social partner has the *same goal* as the learner.

A. Individual exploration

In Fig. 3 we observe that social learning usually outperforms individual learning. However, when the learned affordance is not rare, random and novelty-based exploration have comparably high performance. Individual learning in such cases has two advantages: (1) it does not require social partners and (2) it is less perceptually demanding on the learner in terms of identifying social partners and perceiving actions performed and objects used.

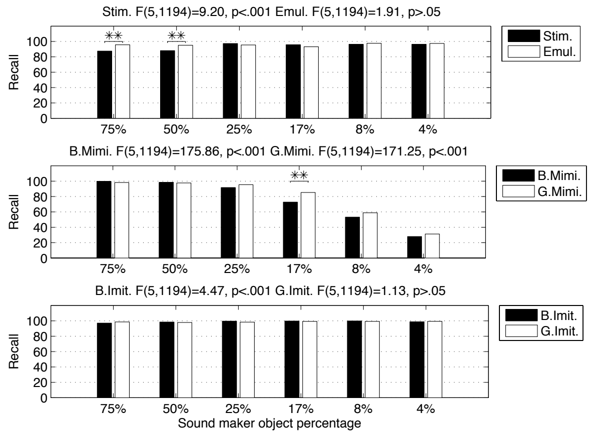
Additionally, individual strategies can do better in environments with high sound-maker frequency when they are allowed to interact for a longer duration. For instance doubling the number of training interactions raises the performance of random and novelty-based exploration to 90-100% in environments with 75% and 50% sound-makers [Cakmak et al., 2009]. Since there's no requirement of a social partner, it's acceptable to perform individual exploration for longer durations to collect more interaction samples.

B. Social exploration: Paying attention to objects

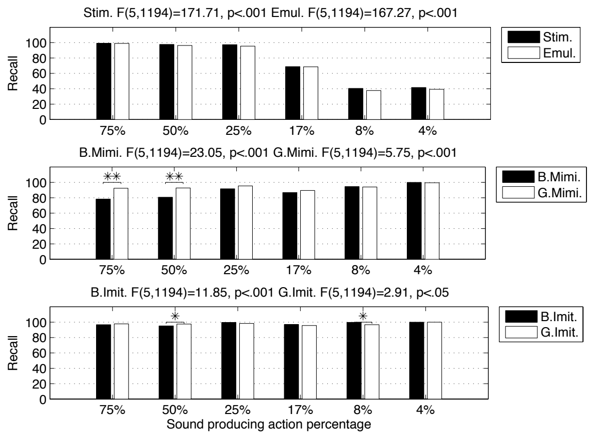
As observed in Fig. 4(a), increasing object rareness does not affect the performance of object focused strategies (stimulus enhancement and emulation) but it significantly reduces the performance of action focused strategies (mimicking). This suggests that when the object with the desired affordance is very rare, it is useful to let the social partner point it out. By randomly exploring actions on the right object the learner can discover affordances.

C. Social exploration: Paying attention to actions

Similarly, when the sound producing actions are rare, doing the right action becomes crucial. Performance of mimicking stays high over reducing sound-producing action frequencies (Fig. 4(b)).

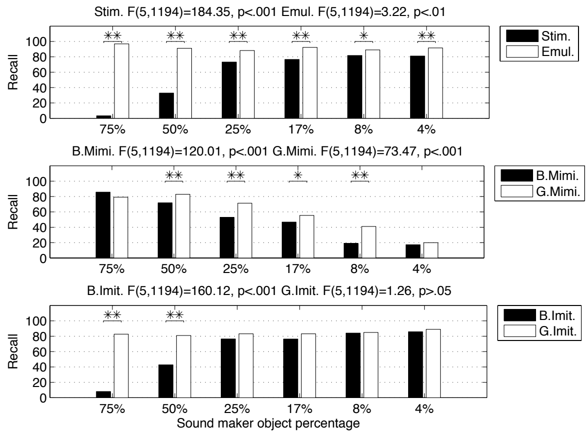


(a)

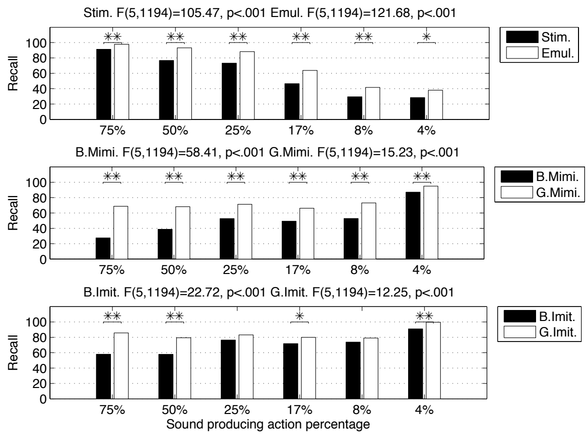


(b)

Fig. 4. Comparison of social learning mechanisms for (a) different sound-maker object frequencies and (b) different sound producing action frequencies. The social partner has the *same goal* as the learner.



(a)



(b)

Fig. 5. Comparison of social learning mechanisms for (a) different sound-maker object frequencies and (b) different sound producing action frequencies when the social partner has a *different goal*.

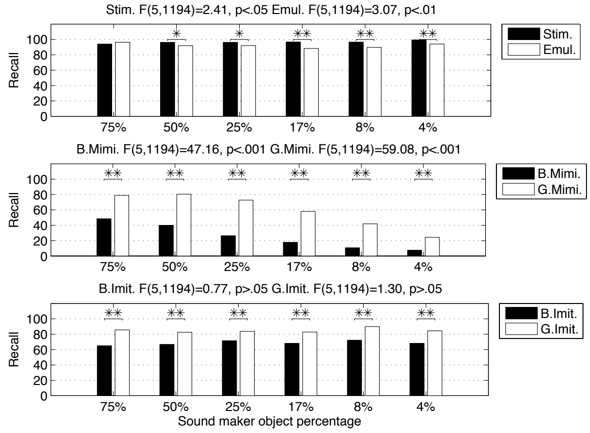
Practically, mimicking will often be more powerful than the object-focused strategies since action spaces are usually larger than object spaces (which are naturally restricted by the environment). For instance, the most salient feature combination may be large-red-square, but if there's no such object the robot may end up choosing small-red-square. Generally, all feature combinations are not available in the environment, but all actions are. In these experiments, action and object spaces had the same number of possible configurations, thus having similar rareness effects.

D. Social exploration: Imitation

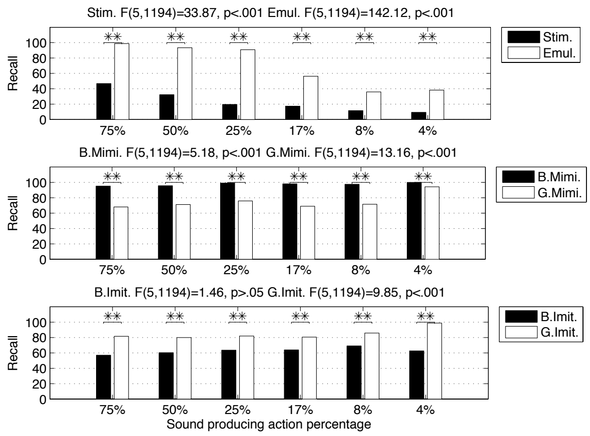
Following from the previous two cases when everything is rare the most powerful strategy is imitation. As observed from Fig. 4 imitation performs well in all environments. This raises a question as to why imitation should not be the default strategy. There are two main disadvantages to always using imitation. First, it is the most computationally demanding for the learner; it requires paying attention to the context and and the action. Second it is also demanding of the demonstrator. For instance in the case where sound-maker objects are rare but the sound producing action is not, the demonstrator can just perform an *object-demonstration* rather than a *goal-demonstration* (Sec. III-C). A robot could be equipped with other means for directing the attention of the learner to the right object without a demonstration. Examples include pointing to the object, pushing the object towards the learner, shaking the object, gazing at the object or putting away all other objects.

E. Social exploration: Paying attention to the goal

The performance of stimulus enhancement and emulation are very similar in Fig. 4. Likewise there are very few significant differences between goal-based and blind strategies for mimicking or imitation. This suggests that when interacting with a social partner with the same goal as the learner, paying attention to the effect of demonstrations is less important. The attention of the learner is already attracted to the object that was interacted with, which happened to also produce sound since a high fraction of the demonstrations do so.



(a)



(b)

Fig. 6. Comparison of social learning mechanisms for (a) different sound-maker object frequencies when the social partner demonstrates the sound-maker objects and (b) different sound producing action frequencies when the social partner demonstrates the sound producing actions without actually producing sound–*focused demonstration*

If the social partner has a different goal we observe that the performance of blind strategies is lower than that of goal-based strategies as shown in Fig. 5. In this case, blindly copying aspects of the demonstration results in an exploration focused on the wrong objects or actions. In other words they are misled to uninformative parts of the context and action spaces. Goal-based strategies, on the other hand, only pay attention to the social partner's useful demonstrations. The rest of the time they randomly explore based on this useful information and thus have a higher chance to discover and gain experience with sound-makers.

In Fig. 6 we observe that the performance of the blind strategies are better than those of the goal-based strategies when the social partner performs focused demonstrations of objects or actions without producing the desired effect. The blind strategies benefit from these demonstrations by being directed to the right parts of their action or context space while the goal-based strategies ignore these demonstrations.

Focused demonstration can be considered a typical kind of teaching behavior. A teacher who is trying to teach a particular action might demonstrate it on a different object. Similarly, a teacher might present objects that are known to have useful affordances to the learner but let the learner discover what actions produce the desired effects on the object. In such cases it is useful to trust the teacher even if the goal has not been observed. By trusting the teacher the learner later comes to uncover the use of copied actions or objects.

F. Asymmetry between object and action spaces

It can be noticed that the performance in similar parts of the object and action space are not exactly symmetric for similar behaviors. For instance in Fig. 5, in (a) at high sound-maker object frequencies the performance of emulation is as high as 90-100%, whereas in (b) at high sound-producing action frequencies the performance of goal-directed mimicking is about 70%. This is due to a subtle difference between the representation of object and action spaces. The action space consists of two independent smaller subspaces corresponding to each action. Learning about the parameters of one action does not provide any information for the other action and therefore both actions need to be explored sufficiently. For instance if the robot is performing a grasp, the values of poking parameters are meaningless. Additionally the robot needs to simultaneously learn which action is useful in a given situation, as well as its parameters. On the other hand interaction with one object provides information about all attributes in the object space since all objects are represented with a value for each attribute. This makes the action space harder to explore than the object space. As a result the performance of object focused strategies in the object space, is better than the performance of action focused strategies in the action space.

G. Validation on the Physical Robots

A simplified version of the simulation experiments were run on the physical robots as described in Section III. Table II gives the results of learning in four different environments for two strategies: stimulus enhancement and blind mimicking. The social partner in this experiment always demonstrates the goal. The given results are the averages over five runs of ten world interactions. The results support our findings from the simulation experiment that the performance of stimulus enhancement is less affected by decreasing sound-maker percentage, while the performance of mimicking is less affected by the decreasing sound-producing action frequency. Furthermore, due to the asymmetry in the action and context spaces we observe that the reduction in the performance of mimicking is less severe.

V. Discussion

As expected from prior work, social learning is better than individual learning, particularly when the learned affordance is rare. In this work we've shown the computational benefits

TABLE II

RECALL RATE IN PHYSICAL ROBOT EXPERIMENTS.

Environment	Stim.	Mimi.
Act.:50%, Obj.:50%	70%	100%
Act.:50%, Obj.:25%	86%	60%
Act.:3%, Obj.:50%	0%	100%
Act.:3%, Obj.:25%	20%	100%

of four biologically inspired mechanisms: stimulus enhancement, emulation, mimicking, and imitation. We find that each social learning mechanism has benefits over the others depending on the environment and the partner's behavior.

If the learner is in an environment where the objects that produce the goal are rare, then the mechanisms related to object saliency (stimulus enhancement, emulation, and imitation) perform best. Furthermore, all are equally good if the partner is actively demonstrating the goal. However, if the social partner is demonstrating other goals, or only one aspect of the goal (either action or object), then emulation and goal-based imitation outperform stimulus enhancement.

Alternatively, in an environment where only a few specific actions produce the goal, then action oriented mechanisms (mimicking and imitation) are best. Again, when the social partner is demonstrating the goal, both do equally well; otherwise, goal-based mimicking and imitation are preferred.

Not surprisingly, goal-based imitation is robust across test scenarios. However, what we have shown is that in various environmental and social contexts, simpler mechanisms can provide benefits on par with imitation. This is an important point for the robot learning community since these alternatives may be easier to implement and less computationally intensive; for example, not requiring full activity recognition.

Additionally, in some scenarios goal-based imitation may not be possible. When the agents have different action repertoires emulation is most useful because the learner may not be able to understand/perform the demonstrated action.

Thus, we argue that to best take advantage of a social environment robots need a repertoire of social learning mechanisms inspired by those seen in biological systems. An interesting area for our future work is to devise a framework in which all four mechanisms can operate simultaneously; the challenge becomes appropriately switching between strategies. A naïve approach could adopt a new strategy when the current one ceases to be informative. A more sophisticated approach might look for social or environmental "cues" that indicate what "kind" of social partner is present.

VI. CONCLUSION

We presented a series of experiments on four social learning mechanisms: stimulus enhancement, emulation, mimicking, and imitation. We looked at the task of a robot learning a sound-making affordance of different objects, while another robot (a social partner) interacts with the same objects. The contribution of this work is the articulation of the computational benefit of these four social learning strategies for a robot learner. The fact that each strategy has benefits over others in different situations indicates the importance of a social learner having all of these strategies available.

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