Social Learning Mechanisms for Robots

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1 Introduction

There is currently a surge of interest in service robotics—a desire to have robots leave the labs and factory floors to help solve critical issues facing our society, ranging from eldercare to education. A critical issue is that we cannot preprogram these robots with every skill they will need to play a useful role in society—they will need the ability to interact with ordinary people and acquire new relevant skills after they are deployed.

Using human input with Machine Learning systems is not a new goal, but we believe that the problem needs reframing before the field will succeed in building robots that learn from everyday people. Many related works focus on machine performance gains; asking, "What can I get the person do to help my robot learn better?" In an approach we call, Socially Guided Machine Learning (SG-ML), we formulate the problem as a human-machine interaction; asking, "How can I improve the dynamics of this tightly coupled teacher-learner system?"

With the belief that machines meant to learn from people can better take advantage of the ways in which people naturally approach teaching, our research aims to understand and computationally model mechanisms of human social learning in order to build machines that are natural and intuitive to teach.

In this paper we focus on a particular aspect of SG-ML. When building a robot learner that takes advantage of human input, one of the design questions is "What is the right level of human guidance?" One has to determine *how much* and *what kind* of interaction to require of the human.

We first review prior work with respect to these questions, and then summarize three recent projects. In the first two projects we investigate self versus social learning and demonstrate ways in which the two are mutually beneficial. In the third

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project we investigate a variety of social learning strategies, implementing four biologically inspired ways to take advantage of the social environment. We see computational benefits with each strategy depending on the environment, demonstrating the usefulness of non-imitative social learning. Taken together these projects argue that robots need a variety of learning strategies working together, including self and several types of social mechanisms, in order to succeed in Socially Guided Machine Learning.

2 Background

Enabling a human to efficiently transfer knowledge and skills to a machine has inspired decades of research. In this section we situate our research with respect to this prior work.

2.1 The Guidance-Exploration Spectrum

When prior work is viewed along a *Guidance-Exploration* spectrum, an interesting dichotomy appears. Prior works that incorporate human input into a Machine Learning process tend to maintain a constant level of human involvement.

Several are highly dependent on *Guidance*, learning nothing without human interaction (e.g., learning by demonstration [9, 6, 14, 2], learning by imitation [29], learning with natural language [20], and via tutelage [25, 21]). In these, the learner does little if any exploration. The teacher must learn how to interact with the machine and know precisely how it needs to perform the task.

Other approaches are almost entirely *Exploration* based. For example, the human may control the reward signal given to a reinforcement learner [33, 15, 12, 31], provide advice [10, 22], provide animal training inspired clicker feedback [4, 17, 28], or control the agent's actions during training [30]. These approaches have the benefit that learning does not require the human's undivided attention. However, they strongly limit how the human can assist the learner and usually require the human to learn how to interact with the machine.

This highlights an important question for systems that learn with human input. What is the right level of human involvement? How much should the system rely on (or require from) the teacher? On the guidance end of the spectrum is a system that is completely dependent on human instruction, and on the exploration end is a system that learns through self exploration with little input from a human partner. Taking inspiration from human learning, we observe that a social learner should be able to operate flexibly along this *Guidance-Exploration* spectrum. Children explore and learn on their own, but in the presence of a teacher they can take advantage of social cues and communication to accomplish more. Thus, we posit that a robot should be able to explore and learn on its own, but also take full advantage of a human partner's guidance when available.

2.2 Social Learning and Robotics

Robotics research has long been inspired by human social learning, and this work has largely focused on one aspect—imitation. This has been called *Learning by Imitation or Demonstration* and works toward robots capable of reproducing demonstrated motor actions [29], learning generalized task representations [26], policies [9] or a proto-language about actions [3].

A body of research is devoted to finding ways to learn the imitative behavior itself, rather than hard-coding it [24, 11]. Some focus on task- or goal-level imitation, reproducing the task not through imitative behavior, but with it's own actions [18, 23, 16].

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 [7], dynamical equations to control the robot's movements [27] or a sequence of primitive actions [1].

We are interested in taking a broader view of social learning and exploring the variety of ways that a social partner influences learning, in addition to imitation.

3 Motivation

Our approach is *Socially Guided Machine Learning*, exploring the ways in which Machine Learning agents can exploit human social learning. This work claims that computational learning systems should make use of human social learning principles because:

1. **It is better for the human:** To learn from people without experience in robotics or machine learning, it is a working hypothesis of this approach that using characteristic aspects of human learning will be the most natural interface. Several studies show that humans inherently and dynamically provide *social scaffolding* for learners, and do not realize they are engaging in structuring the learning process. Greenfield describes studies, of children learning language and girls learning to weave [13], where the teachers engage in a complex process of dynamically adjusting their support of the learner based on skill level and success. The entire time the teachers are unconscious of the process or method by which they are teaching. Thus, the partnership of social learning is an interaction that people fall into intuitively.
2. **It is better for the machine:** This point is generally less intuitive, but one way to think of it is that social interaction provides biases and constraints that simplify the problem for the machine. Thus, social learning leads to a more efficient and

robust machine learning process. We have shown examples of this in our prior work [33], and one of the claims in this paper involves the mutually beneficial relationship (from a Machine Learning perspective) of self and social strategies.

Human development provides insight into how to approach this sizable SG-ML problem. Children naturally interact with adults and peers to learn new things in social situations. Throughout their development, children's learning is aided in crucial ways by the structure and support of their environment and especially their social environment.

Situated learning is a field of study that looks at the social world of a child and how it contributes to their development [19]. In a situated learning interaction, a good instructor maintains a mental model of the learner's understanding and structures the learning task appropriately with timely feedback and guidance. The learner contributes to the process by expressing their internal state via communicative acts (e.g., expressing understanding, confusion, attention, etc.). This reciprocal and tightly coupled interaction enables the learner to leverage instruction to build the appropriate representations and associations.

This situated learning process stands in contrast to typical scenarios of machine learning which are often not interactive nor intuitive for the human partner. As described in the previous section, prior work often resides at a static point along the Guidance-Exploration spectrum, whereas human social learning is a dynamic process of interactive scaffolding. Additionally, the human social learning process includes much more than imitation, which has been the focus of robotics research.

In this paper we explore both of these issues. We present two projects that show the mutually beneficial relationship of self and social learning, and argue that a successful social robot learner will actually need multiple mechanisms to operate along the full Guidance-Exploration spectrum. We present a third project that illustrates the benefits of several non-imitation social learning mechanisms, showing ways that a robot can take advantage of the multitude of ways that a social partner can influence the learning process.

4 Self versus Social Learning

Much of our work to date in SG-ML has focused on comparing self and social robot learning, to prove that social learning with an everyday human (not a system designer) provides a performance benefit over self learning. The conclusion we have been able to draw multiple times is that "self" and "social" learning strategies are not diametrically opposed. From a computational perspective, each provides different benefits for the robot learner. In this section we present two projects that illustrate this point, each with a different robot platform and learning approach.

Fig. 1 The MIT Leonardo robot has more than 65 degrees of freedom and its expressive capability was specifically designed for social interaction. Pictured here, is Leo with a human partner exploring the toy puzzle box.

4.1 Self and Social Reinforcement Learning

Our first example of self versus social robot learning uses a hierarchical Reinforcement Learning (RL) approach [32]. Through exploration the robot builds a representations of tasks (temporally extended actions) for bringing about various novel states/events in the environment. As this task set grows with experience, the system has mechanisms for generalizing the state representations of its tasks. For example, if it learns a task about pressing a button to turn a light on. As it learns the policy (value function) for this task, it may see other trajectories to the goal that allow it generalize that the color feature of the button is not important for the task.

The system has several mechanisms for incorporating human input to this RL process (e.g., attention direction, action suggestion, and positive/negative feedback). This project was completed on the MIT Leonardo platform (Fig. 1).

4.1.1 Experiment

We conducted an experiment with people teaching the Leonardo robot, and compare this to the robot learning on its own in the same environment. The experimental scenario is a playroom, in which Leo has toy puzzle boxes. The boxes have a button a slider and a switch as inputs, and they are able to change color, open/close, and play a song. These effects come about after the correct sequence of actions are done to the box (e.g., pressing the button until the light is white and then moving the switch left will open the lid).

To show experimentally which aspects of the learning process are influenced by a non-expert human partner's interaction we collected data from two types of learning sessions: SELF—the robot learning on its own; and GUIDED—the robot learning with a human teacher. We collect several independent measures during the learning sessions with nine human subjects. We then compare means between the two groups with t-tests in order to understand some specific details of how guidance and self learning differ.

Experimental subjects were shown the functionality of the puzzle box and told that their goal is to help Leo learn about the box. They are told the robot is able to do some actions on the toy puzzle box, and once turned on, it will start exploring what it can do with the box. They are told they can help Leo by making action

Table 1 Differences between Self and Guided Learning

Measure	Mean (SELF)	Mean (GUIDE)	T-Test Results
# Actions to first goal in learning session	11.2	3.56	$t(19) = 2.11$; $p < 05$
Size of resulting *Tasks* set	10.4	7.55	$t(19) = 7.18$; $p < .001$
# Tasks for T_{Blue}	0.833	1.333	$t(19) = -2.58$; $p < .01$
# Tasks for T_{Open}	1	1.77	$t(19) = -1.83$; $p < .05$
# States can reach T_{Open} in post-experiment	.58	1.56	$t(19) = -2.88$; $p < .01$
# Actions to reach T_{Blue} in post-experiment	2.66	1.69	$t(19) = 2.19$; $p < .05$

suggestions, by naming aspects of the box, and by testing that these named aspects have been learned. Their goal is to make sure that Leo learns to do three specific things: T_{Blue}, Make the light blue; T_{Open}, Make the lid open; T_{Song}, Make the song play. None of the human teachers focused on T_{Song} (the most complex task), thus these results center on the tasks that people tried to teach, T_{Blue} and T_{Open}.

4.1.2 Results

During the learning session, we log several measures to analyze the effect of guidance on the learning process. Additionally, the efficacy of the learned task sets was tested in simulation afterwards (detailed below). The differences between the self learning (SELF) and guided learning (GUIDE) cases are summarized in Table 1. In all we tested 12 hypothesized differences between the two groups, and we detail the six significant differences found.

The human partner is able to guide the robot to the desired goal states faster than happens on its own. This is seen in the difference between groups in the number of actions to the first encounter of any of the experiment goals. The average for GUIDE, 3.56, is significantly less than the average for the SELF condition, 11.2. Thus, people were able to utilize the social scaffolding mechanisms to focus the robot on aspects of the environment that they wanted it to learn. This is also supported by qualities of the resulting task set that is learned. In the GUIDE condition, the resulting task sets were more related to the experiment goals (i.e., one of the three experimental goals is true in a task's goal state). We see a significant difference in both the number of tasks related to T_{Blue} and T_{Open} (see Table 1).

Finally, the GUIDE group learns a better task set for achieving the experiment goals. In the post analysis of the learned tasks, we tested each task set from a test suite of initial states, and measured their ability to achieve the experimental goals. Each experiment goal has a different test suite of five initial states. For each of the learned task sets, we record the number of actions needed to reach each of the experimental task goals from each of the test states. We see some significant differences in the generality of the learned tasks. The average number of states that the GUIDE task sets could reach the T_{Open} goal, 1.56, was significantly better than the SELF condition, 0.58. And though we didn't find this difference for the T_{Blue} goal, we do

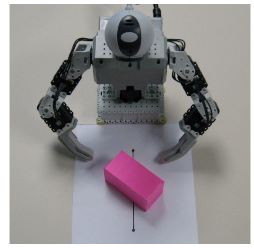


Fig. 2 Junior is a Bioloid robot configured as an upper torso humanoid with a Webcam head. It is approximately 10 inches high. It has 8 degrees of freedom, which enables arm movements, torso rotation and neck tilt.

see that the GUIDE condition is significantly faster at achieving T_{Blue} in the post analysis than the SELF condition, 1.69 versus 2.66. Thus, human guidance leads to task sets that are better at achieving the experimental goals at a later time. Focused and repeated experience with these goals resulted in more generalized task representations.

In self-learning on the other hand, the robot had a broader experience, serendipitously learning aspects of the environment that the human was not focused on teaching. While not what the human had in mind today, this knowledge about the environment could be advantageous in the future. Thus, we conclude that self and social learning are mutually beneficial in this learning context.

4.2 Self and Social Supervised Learning

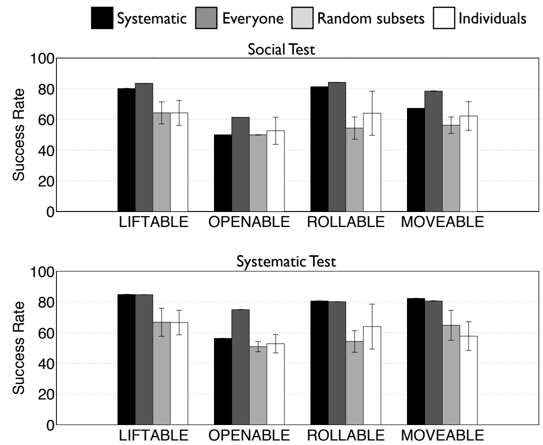
While Leo used high-level task learning and an RL approach, in our second example the Junior robot (Fig. 2) learns about object affordances through a supervised learning approach (Support Vector Machines) [34].

4.2.1 Experiment

Junior learns about a set of five simple objects with different geometrical shapes and bright, distinct colors. It has two actions it can perform on the objects—a single arm *poke* action, and a double arm *grasp* action. When an object is detected in the workspace, Junior will try one of its actions on the object. Action effects are perceived by the robot as changes in the object state. The set of possible affordances for the five objects is: lifted, opened, rolled, moved, tipped, or no effect. A two-class SVM is trained for each type of effect, using the state of the object as the feature space and the affordance as the target value.

Our experiments with Junior focus on comparing self and social learning of object effect classifiers, using two modes of affordance learning: *social* and *non-social*. In the non-social case the workspace and the object configuration space are exhaustively explored with both actions. Each object is moved at 0.25 inch intervals on the workspace in several possible orientations. This results in 756 object interaction

Fig. 3 Learning results: Prediction success of classifiers trained with the systematic (non-social) data and the social data, on (Top) social test data and (Bottom) systematic test data. Values averaged over 10 randomly sampled test sets.



samples. In the social case, a human teacher controls which objects the robot interacts with, and decides where and how to place the object in the workspace. We collected data in this social case from 14 subjects. In the experiment introduction, subjects were told that their goal is to help Junior learn what it can do with the five objects. They were asked to place one object at a time in the workspace, and the experiment duration (number of interaction samples) was the subjects' decision.

4.2.2 Results

This experiment lets us compare the effect of social data collection on a supervised learning process. Separate SVMs are trained with the data sets collected from the social and non-social process of exploring the five objects.

Fig. 3 compares the average successful prediction rate for classifiers with four different training data sets: (i) **systematic**: the complete set of examples collected non-socially, (ii) **everyone**: the combination of examples provided by all 14 individuals, (iii) **random subsets** of the systematic data (size equal to the average number of examples given by one subject), and (iv) **individuals**: the data sets obtained by individual subjects in the experiment. Two test data sets (social and non-social) are created by randomly sampling equal numbers of positive and negative examples from either the non-social or the social data set.

Our first observation is that the complete data sets (systematic and everyone) generally perform better than the smaller data sets (random subsets and individuals). Thus, the number of samples given by one individual in a single session may not be sufficient for learning everything. This points to the importance of self exploration (for collecting large data sets with systematic experiments) as well as long-term training by individuals (multiple sessions) or by multiple teachers. Nonetheless, the variance in the individuals' performance indicates that some individuals were able to get close to the performance of the complete data sets.

A second observation is that social learning provides the opportunity to see rare affordances; outcomes that occur in very few object configurations. For example, one of the objects is a box with a lid Junior can open. However, this occurs for the grasp action in only one orientation and limited locations. Depending on the resolution with which the objects are displaced in during the systematic exploration, the opening effect could easily be left out of the non-social data set. On the other hand if resolution is increased to insure the effect is seen, the number of opening examples becomes relatively very few since the number of non-opening samples increases. Hence it is hard to learn a rare affordance from systematic data.

A social setting can provide the adaptive resolution to overcome this problem. Humans experiment with the box object by varying the distance in very small steps within the range that it can be opened, but they provide sparse samples outside this range. Similarly, they provide more examples of the box being in its normal orientation compared to other orientations in which it cannot be opened.

This leads to better performance for the social training sets on rare affordances (e.g., opening and rolling), for both test cases. Since these affordances are rare in the non-social data set, it results in pessimistic classifiers that mostly predict a negative outcome. With more frequent affordances such as lifting and moving, the social data set is on par with the non-social training set.

On the other hand, social experiments may fail to capture affordances that occur in the non-social case. For example 29% of the subjects did not notice the tipping effect of the poking action on some objects, thus providing no examples of it. Similarly, most subjects did not notice that Junior could grasp objects placed very close to it. They placed objects at a comfortable distance at which a more natural grasp would occur. These oversights may occur due to people's inexperience with the robot as well as the inexperience with the objects. Self-exploration can therefore be important in discovering affordances that are not predicted by the human. Again, this points to the mutually beneficial relationship between self and social learning.

5 Varieties of Social Learning

Convinced from these previous studies that a robot needs both self and social learning working side-by-side, the third project investigates a range of social learning strategies. This work was completed on a team of Junior-like robots we call the Robot Playmates (Fig. 5) [5].

We are interested in the variety of ways that a social partner influences learning. Inspired by biological systems [35, 8], we implemented the following four social learning mechanisms: *Stimulus (local) enhancement* is a mechanism through which a learner is drawn to objects others interact with. *Emulation* is a process where the learner witnesses someone produce a result, but then employs their own action repertoire to produce the result. *Mimicking* corresponds to the learner copying the actions of others without an appreciation of their purpose. *Imitation* refers to reproducing the actions of others to obtain the same results with the same goal.

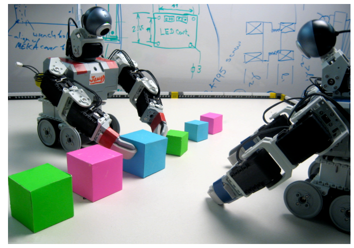


Fig. 4 The Robot Palymates are upper torso humanoids on wheels built from Bioloid kits and Webcams. Their 8 degrees of freedom enable arm movements, torso rotation and neck tilt. The wheels are used to navigate the workspace.

5.1 Experiment

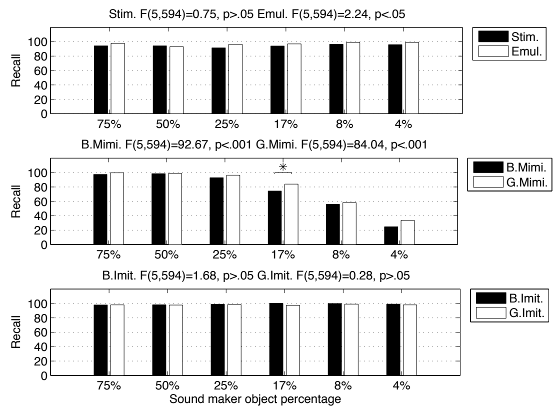
Similar to the Junior project, the learning problem is affordance classifiers. In this case there are objects with discrete attributes: *color*, *size* and *shape*, and one hidden property of *sound-maker* that is apparent only when the object is moved. Again the robots have two actions *poke* and *grasp*, which now have the discrete parameters (i) acting distances and (ii) grasp width or (iii) poking speed.

We conducted a series of experiments, each collects a data set of experience which is then used to train a sound-maker SVM classifier. The SVM inputs are the perceived object features and the actions parameters performed. The prediction target is whether or not this context/action produces sound.

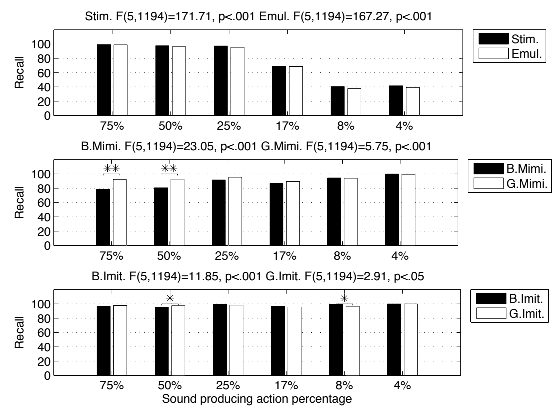
In each experiment the learner uses a particular exploration strategy. A strategy is implemented as an attention mechanism, where each object attribute and action parameter has a corresponding saliency. The robot always performs the most salient action on the most salient object. Each strategy has a different rule for updating saliencies after every interaction:

- Stimulus Enhancement: The robot prefers to interact with objects the playmate has interacted with. After every observed interaction, it increases the saliency of attributes of the object the social partner has interacted with and decreases others.
- 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 set randomly.
- Mimicking: This strategy involves copying the actions of the social partner. We implement a version in which the learner mimics every action (blind) and one where it mimics only after observing the goal.
- 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: the learner always imitates its social partner (blind) or only after observing the target goal.

In order to compare these mechanisms we use a controlled learning environment and investigate two dimensions of the space. (1) The rarity of the learning target (sound-making). This can be due to the object (feature) space or the action space, and we differentiate between these two in our analyses. (2) The behavior of the social partner. In these experiments the social partner is another robot, which allows us to systematically change the behavior of the social partner to explore the effect



(a)



(b)

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

this has on the different strategies. The social partner behaviors that we focus on here are *same-goal* (where the partner demonstrates sound-making in 60% of its interactions) and *different-goal* (sound occurs in only 20% of the interactions).

5.2 Results

We see that each strategy leads to different learning performance in different environments. When the rareness of the target is due to the object space, then the mechanisms related to object saliency (stimulus enhancement, emulation, and imitation) perform best. In Fig. 5(a), the mimicking performances drops off with object rareness while performance of the other strategies remain high. These three all do equally well with the same-goal social partner. However, if the 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 because they pay attention to the effects of the partner's action to ignore demonstrations unrelated to the target learning goal.

Alternatively, in an environment where only a few specific actions produce the goal, then action oriented mechanisms (mimicking and imitation) are best (Fig. 5(b)). Again, when the social partner is demonstrating the goal, both do equally well. Otherwise, imitation is preferred since it pays attention to effects.

Thus, it is not surprising that nature endows humans and animals with a variety of mechanisms for taking advantage of social partners in the learning process. Our computational analysis finds that each serve a different purpose, and have benefits over the others depending on the rareness of the learning goal and the behavior of the social partner.

6 Conclusion

Our research in Socially Guided Machine Learning aims to understand and computationally model mechanisms of human social learning in order to build robots that are natural and intuitive to teach. In this paper we have summarized three recent projects to this end.

In the first two projects we compare self and social learning and find that the two are mutually beneficial. This confirms that rather than remain at a static point on the Guidance-Exploration spectrum, what is desired is a system that dynamically operates along this range. We want a robot with self and social learning working in concert, that learns on its own but is able to take advantage of a social partner when they are present.

Additionally, we have shown the computational benefits of taking advantage of a social partner in a variety of ways. In the third project we implemented four biologically inspired ways to leverage the social environment. We see benefits of each strategy depending on the environment.

Perhaps not surprisingly, imitation is robust across all the test environments. Thus, one might conclude that it is best to only equip a robot learner with the imitation strategy. However, there are a number of reasons that imitation-only is not the best approach to robot social learning. Imitation is not always possible, for example when the partner has a different morphology. Additionally, requiring full demonstrations may be a burden for the teacher. The learner should be able to make use of full demonstrations when available, but as our results have shown social learning is more than just demonstrations. In various environmental and social contexts, simpler mechanisms can provide benefits that are on par with imitation. Using non-imitative mechanisms in conjunction with imitation learning can let a robot use more of the teacher's input, benefitting from their presence and interactions in the environment even when they are not actively giving demonstrations.

Taken together these projects argue that robots need a variety of learning strategies, including self and several types of social mechanisms, in order to succeed in Socially Guided Machine Learning. Our future work is exploring ways to incorporate all of these mechanisms into a single robot learning framework.

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