Learning about Objects with Human Teachers

Andrea L. Thomaz
Georgia Institute of Technology
School of Interactive Computing
85 5th Street NW, Atlanta, GA 30308
athomaz@cc.gatech.edu

Maya Cakmak
Georgia Institute of Technology
School of Interactive Computing
85 5th Street NW, Atlanta, GA 30308
maya@cc.gatech.edu

ABSTRACT
A general learning task for a robot in a new environment is to learn about objects and what actions/effects they afford. To approach this, we look at ways that a human partner can intuitively help the robot learn, Socially Guided Machine Learning. We present experiments conducted with our robot, Junior, and make six observations characterizing how people approached teaching about objects. We show that Junior successfully used transparency to mitigate errors. Finally, we present the impact of "social" versus "non-social" data sets when training SVM classifiers.

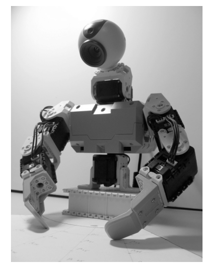


Figure 1: Junior—our robot platform.

1. INTRODUCTION
Our research is motivated by the promise of robots that operate and assist people in human environments. It is reasonable to assume these robots will need to learn during their deployment, since pre-programming every skill needed is infeasible. In our view, robots should be able to do some learning on their own, but they will also need to learn interactively from everyday people–who are likely unfamiliar with robotics and Machine Learning (ML). In prior work, we began exploring how self-exploration and guided learning can be mutually beneficial [17]. In the work presented here, we aim to understand a teacher's role in physically interacting with the learner and the workspace.

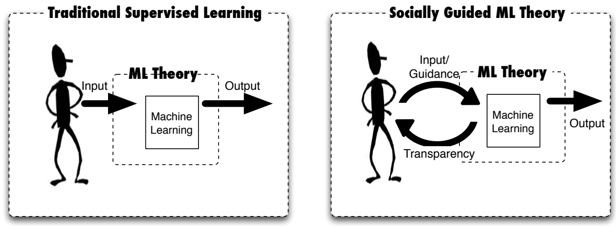
In a new environment, a general task for the robot is to learn about the environment's objects and what actions/effects they afford–Affordance Learning [11]. We take a Socially Guided Machine Learning (SG-ML) approach to this task. In this paper, we first situate our approach in the context of prior work. We then present social learning experiments conducted with our robot platform (Fig. 1), yielding three contributions: (1) We characterize how people taught Junior about objects, and how this differs from a systematically collected "non-social" data set. (2) We show that Junior was able to use a gazing behavior to improve the interaction and mitigate errors. (3) We show the impact of "social" versus "non-social" data sets in training Support Vector Machine (SVM) classifiers.

2. BACKGROUND
For years researchers have been inspired by the idea of efficiently transferring knowledge from a human to a machine. In most prior work, systems were not tested with everyday persons; nonetheless, a review characterizes the ways machine learning systems have leveraged human input.

Machine learns by observing human: Several systems deal with the scenario where a machine learns by passively observing a human: Learning assembly tasks [9], learning a peg-in-hole task[19], learning a task reward function [1]. Generally, our goal is to have a more interactive system, that learns in real-time from everyday people, taking advantage of how such users will naturally provide instruction.

Human explicitly directs action of the machine: In many works, the human directly influences the robot's actions to provide a learning experience: learning tasks by following a human [12], by tele-operation [15, 7], by physical interaction [3], by selecting demonstration actions in a GUI interface [5], or making action suggestions to a Reinforcement Learning agent [10, 16]. These approaches are more interactive than learning by observation and more closely resemble our goals. However, most require the human to learn how to correctly interact with the machine and to know precisely how the machine should perform the task.

Human provides high-level evaluation, feedback, or examples to a machine: In other systems a human in-



(a) (b)

Figure 2: SG-ML explicitly has the human "in the loop", in contrast to standard supervised ML.

fluences the experience of the machine with higher level input. For example, providing feedback to a reinforcement learner [8, 13], or examples to an active learning system [4, 14]. Again, the human acts as an explicit teacher for a specific task, *i.e.*, the human provides input in a form that is designed explicitly for the learning system rather than the human.

3. APPROACH

In much of the work mentioned above, the primary motivation for using human input is to achieve performance gains for the machine. Our approach, *Socially Guided Machine Learning*, advocates designing for the performance of the complete human-machine social learning system. This reframes the machine learning problem as a human-machine interaction, and allows us to take advantage of human teaching behavior to construct a learning process that is more amenable to the human partner.

In general, supervised Machine Learning has a human provide input examples to the learner, which performs its task and provides some output. Alternatively, an SG-ML view of learning models the complete human-machine system (characterized in Figure 2). An interaction approach to machine learning forces us to consider many new questions highlighted by this simple diagram. We need a principled theory of the content and dynamics of this tightly coupled process in order to design systems that can learn efficiently and effectively from everyday users.

Input Channels: An SG-ML approach asks: "How do humans want to teach?" In addition to designing for what the machine needs in learning, we need to understand what humans will naturally try to communicate in their everyday teaching behavior. We can then change the input portion of the ML training process to better accommodate a human partner. In Section 5.1, we present a characterization of how people approach the task of teaching Junior about objects.

Output Channels: An SG-ML approach asks: "How can the output of the learning agent improve the performance of the teaching-learning system?" In an interaction, a 'black box' learning process does not help the teacher improve the quality and relevance of their instruction. By communicating internal state, *e.g.*, revealing what is unclear, the agent could greatly improve the experience, guiding the teaching process. In Section 5.2, we show that Junior can effectively use eye gaze as a transparency device in the learning process to elicit the desired support from the human teacher.

We claim there are two reasons that computational learning systems should make use of social learning principles:

(1) Better for the human: To learn from everyday people, a working hypothesis of SG-ML is that using aspects of human social learning is the most natural interface. Several studies show that humans inherently and dynamically provide *social scaffolding* for learners. Greenfield describes studies, of children learning language and learning to weave [6]. Teachers dynamically adjust the support provided based on skill level and success, and they are unconscious of the process or method by which they are teaching.

Thus, the partnership of social learning is an intuitive interaction for people. We see this in the work presented here, where people respond consistently and appropriately to the robot's use of gaze as a social cue (Section 5.2).

(2) 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 can lead to a more efficient and robust machine learning process. We have shown examples of this in prior work [18]. Additionally, in Section 5.3 we show the positive impact of social learning in the context of learning SVM classifiers.

4. RESEARCH PLATFORM

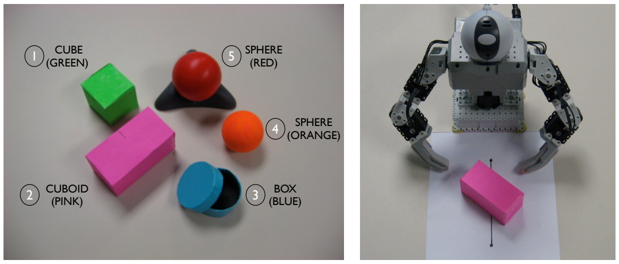
4.1 Hardware

Our platform for this research is Junior, a Bioloid robot configured as an upper torso humanoid with a Webcam head (Fig. 1). It is approximately 10 inches high. It has 8 degrees of freedom, which enables arm movements, torso rotation and neck tilt. Junior's action set consists of two actions: *poke*–a single arm swing (*e.g.*, for batting or pushing objects) and *grasp*–a coordinated swing of both arms. Both actions are parametrized with the height and distance of the object to which the action is directed.

We use the OpenCV Library to track objects with Continuously Adaptive Mean Shift based blob tracking for predefined colors. The state of an object in the workspace is specified with several blob properties. This includes measured properties: *distance* (obtained by the neck position required to center the blob in the image, assuming it is on the table), *color*, *area* (number of pixels), *orientation*, *height* and *width* (length of major and minor axes); and derived properties: *eccentricity* (ratio of major and minor axes) and *squareness* (ratio of connected component area to the area of the minimum enclosing rectangle). These are features common in object affordance learning [11].

4.2 Software

Junior's behavior system is implemented in C5M, a cognitive architecture for interactive characters [2]. Junior's interaction with the objects is regulated with three behaviors. When there's no object in the visual field a *search* behavior randomly changes the head tilt until an object is in view. Then a *fixation* behavior centers the object in the visual



(a) (b)

Figure 3: (a) Junior's object set in the experiment (b) Junior's workspace

field. The object interaction behavior triggers one of the two actions when an object is stationary in the center of visual field for about two seconds.

Junior also has a *gazing* behavior triggered by the *error* situation, which occurs when the object is stationary but cannot be centered in the visual field due to a joint limit (*i.e.*, objects too far or too close). The gaze action consists of moving the neck tilt to the upper limit and moving back to the starting tilt angle; thus, it makes the assumption that a person is sitting in front of it.

4.3 Learning Framework

In order to study learning about objects, we employ an affordance learning paradigm. Junior interacts with objects to learn the effects of its actions on various configurations of each object. Junior obtains interaction experience tuples during an exploration phase. Each tuple is of the form [initial object state; action; perceived effect/affordance], a common representational framework used in affordance learning [11]. This data set of experience is used to learn affordance classifiers to predict action outcomes.

Junior learns about a set of five simple objects with different geometrical shapes and bright, distinct colors (Fig. 3(a)). The robot sits on a tabletop, and its workspace for our experiments is a 5 inch straight line in front of it (Fig. 3(b)). Action effects are perceived by the robot as changes in the object state. We hand labeled each sample with the most obvious affordance category. The effects for grasping are (i)*lifted:* the object moved upwards until it was dropped, (ii)*opened:* the cover of the box separated from the bottom, and (iii)*other:* the object slipped and fell down, was moved away or was thrown away during grasping. The effects for poking are (i)*rolled:* the object kept moving in the poking direction after contact was lost, (ii)*moved:* the object moved (displaced, oriented or both) in the poking direction until contact with the object was lost, and (iii)*tipped:* the object fell over around one point. Both actions have the category of (iv)*no effect* in which the object does not move at all.

5. EXPERIMENTS

Our experiments with Junior's affordance learning are motivated by the following three questions:

1. What is the nature of a human teacher's input in the process of learning about objects in the environment?
2. How can the robot dynamically influence the teacher, to provide a better input signal, improving its own learning environment?
3. What impact does a socially collected data set have on the underlying machine learning processes?

We study two modes of affordance learning to explore these questions: *social* and *non-social*. In the non-social case (also referred to as the "systematic" 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. We consider 2 orientations for the cube, 5 for the cuboid, 9 for the box and one for each sphere. The cube can be parallel (flat surface facing Junior) or diagonal; the cuboid can be standing or lying (long edge normal or parallel to table), different edges facing Junior or diagonal; and the box can be in its normal configuration (cover on top), or its two pieces separately, round surface facing upwards, facing the side or facing Junior. This results in a total of 756 object interactions in the non-social case.

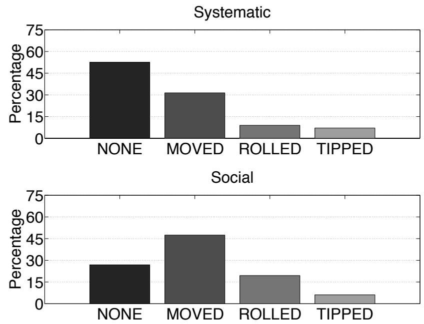
In the social case, a human teacher controls which objects the robot interacts with, and decides where and how to place the object in the workspace. We collected data in this social case from 14 subjects, recruited from the campus community (78% male). In the experiment introduction, subjects were informed about Junior's exploratory behavior and told that their goal is to help Junior learn what it can do with the five objects. They were told not to move the object once Junior has started an action, and that the action ends when Junior's arms are back to their idle position. They were asked to place one object at a time, horizontally centered on the line indicating the workspace. The experiment duration (number of object interactions) was the subjects' decision.

Junior's torso rotation is restricted to the center position and not used in the search and fixation behaviors. Therefore, fixation consists of vertically centering the object in the image and any horizontal deviation results in an error condition, triggering the gaze behavior. Additionally, action arbitration is avoided to make sure that the subject knows what action Junior will execute next when they are configuring the workspace. Thus, each subject started experimenting with one action and decided when to switch to the second action (the action presented first was counter balanced across subjects). Subjects were not given any information about Junior's gazing behavior. In half of the social learning experiments the gazing behavior is turned off, so we have gaze and no-gaze groups.

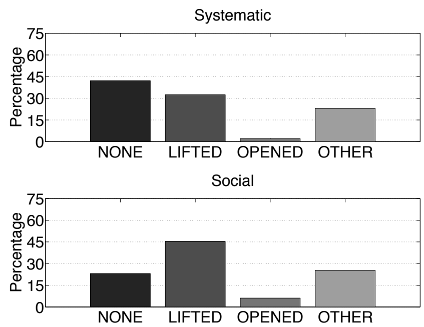
We collected video of the interaction, and people were asked at the end of the experiment to answer 25 questions. The following sections detail our analysis of the data with respect to the three research questions raised above.

5.1 How do people teach?

We start by characterizing the data provided by human teachers compared to the systematically collected data. This



(a) Poke



(b) Grasp

Figure 4: Distribution of effects in the non-social and social cases, for each action.

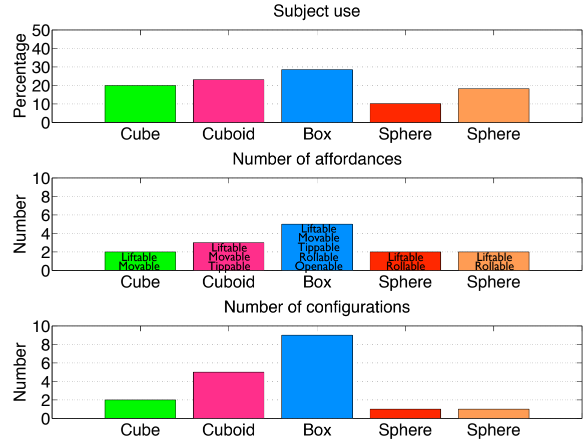


Figure 5: (Top) Dist. of examples given for each object (Middle) Number of affordances of each object (Bottom) Number of configurations of each object.

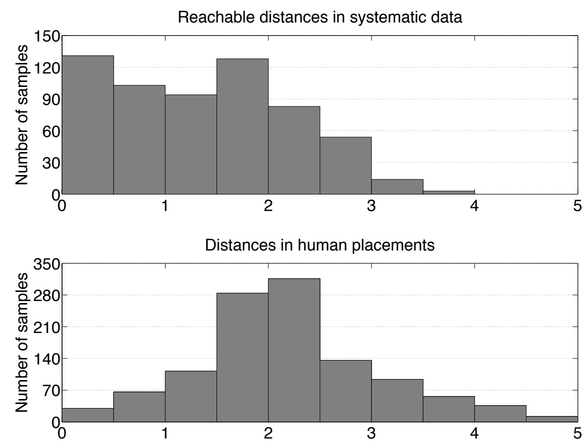


Figure 6: (Top) Histogram of reachable distances, taken from systematic data (Bottom) Histogram of distances where subjects placed objects.

section details six observations about how people approach the task of teaching Junior about objects.

5.1.1 Balance of Positive/Negative Examples

Data sets in the social case were more balanced in terms of positive/negative examples than the non-social case. Fig. 4 gives the distribution of effects seen for actions on objects in the social and non-social cases. For both actions the percentage of the *no effect* category is much lower in the social case (bottom graph in Fig 4 (a) and (b)), and common effects such as *lifted* or *moved* is higher. Rare effects like *rolled* and *opened* are approximately doubled in the social case.

This is a result of people's choice of orientation and location. They presented more examples of objects in orientations that have more affordances. For example, for grasping, presenting the cube in a parallel orientation (61%) rather than diagonally; and presenting the box with the cover on top (43%) as opposed to the other 8 configurations. Similarly, people mostly placed objects easily within reach (Fig. 6).

5.1.2 Example Quantity Proportional to Complexity

The quantity of examples people gave for an object was proportional to object complexity. The top graph in Fig. 5 shows the distribution of examples for each object, and the other graphs show that this distribution was proportional to the object's affordance and configuration complexity.

Number of examples is primarily aligned with the number of affordances an object has. For instance, the blue box has a much larger number of configurations compared to other objects (Fig. 5 bottom graph); however, the extra configurations do not add proportionally as many affordances. Accordingly, people gave the most examples for the box object, but in relation to number of affordances not configurations.

Another observation of the social data set, is that there are more samples of the orange sphere compared to the red, though they both have just one configuration and afford rolling and lifting. Information not captured in the distribution of affordances is how easily they are afforded. The two spheres differ not only in size/color but also in texture and weight. The small size and rough texture of the orange sphere makes it liftable in a larger range compared to the polished surface and high weight of the red sphere. Therefore, people's distribution of examples reflects their perception of affordances through properties not observable to the robot. They take a broader view, *i.e.*, not just afford/not afford, but how easily it is afforded.

The questionnaire supports this attention to affordance com-

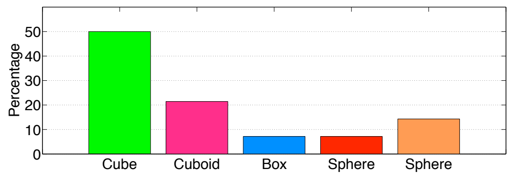


Figure 7: Distribution of starting object choice of subjects for the grasping action.

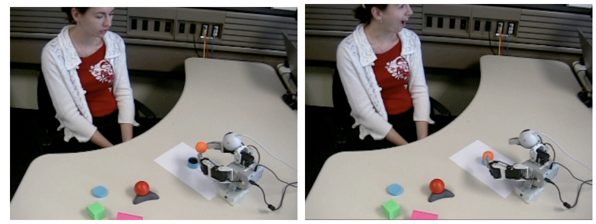


Figure 8: The basket affordance

plexity. When asked open questions about whether they followed a certain order or emphasized any objects, over half of the subjects said no. However, several talked about objects being "boring," "interesting," or "fun." Thus, structuring complexity seems to be an intuitive approach to the task of teaching, even if it was not a conscious effort.

5.1.3 People Start Simple

In addition to examples being proportional to complexity, people start with simple examples, not complex one. Fig. 7 gives the distribution across subjects of starting object choice for the grasp action. The green cube followed by the pink cuboid are most popular, both of which have flat surfaces making them relatively easy to grasp. The orange sphere also has a higher rate than the other two objects for being light and having a rough surface. The starting samples are also easy in terms of location; 86% of the subjects started by placing an object within Junior's reach.

5.1.4 Structured in Object Chunks

The data provided by humans is also distinguishable from the systematic data in the order in which objects are presented. People focus on one object at a time rather than switching between objects. Moreover, 85% of the chunks end with positive examples (examples in which the action has some effect different from "other") which is considerably higher than the overall percentage of positive examples (70%).

In the questionnaire, when asked about teaching strategy, one person described this "chunks" concept, saying they stayed with an object until something significant happened. Most people claimed no strategy, but when asked "Did you present the same object several times? Why?" everyone agreed they did the chunking. Several described staying with one object until succeeding to demonstrate the affordance. Thus people provided key environmental scaffolding, focusing on one object until achieving at least one positive example.

5.1.5 Pointing out Rare Affordances

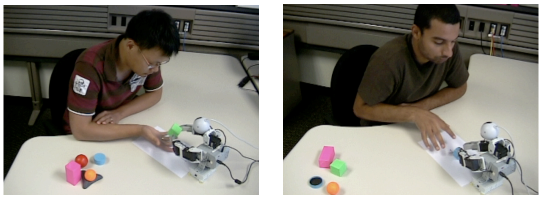
Social learning provides the opportunity to see rare affordances; outcomes that occur in very few object configurations. For instance, opening the box occurs for the grasp action in only one orientation and in a limited range of locations. Depending on the resolution with which the objects are displaced 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 are multiplied. 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 with 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 (Sec. 5.1.1). This adaptive resolution becomes crucial with increasing number or complexity of objects. For instance, one of our subjects discovered the *basket* affordance while experimenting with two objects: the bottom of the box (a container) and a sphere (Fig. 8). When the sphere is placed in front of the container, Junior grabs it and consistently drops it into the container. Capturing this affordance with a systematic experiment, would require experimenting with combinations of two objects in different relative positions and orientations. This would produce roughly 67,000 experiments and approximately 5 of these would result in the basket outcome.

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 (Fig. 6). 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. This points to the mutually beneficial relationship between self and social learning.

5.1.6 Help in Parsing Action Goals

A final observation about the social learning case, is that people's action can help the robot parse its own actions in a goal oriented way. Our instructions explicitly asked subjects not to interrupt Junior's actions and informed them that the end of an action is when its arms go back to their starting position. We observed that this instruction was often violated. Instead of waiting, subjects started to reconfigure the workspace as soon as the effect of the action was complete or definite. For instance some subjects placed their hands below a lifted object in order to catch it as it's dropped, taking it away before the action finished (Fig. 9(a)). Similarly, when the action has no effect on the object several



(a) (b)

Figure 9: Subjects' goal directed parsing of actions. (a) Interrupting trial by handling the object before action completes (b) Interrupting trial by taking away object when it's clear there will be no effect.

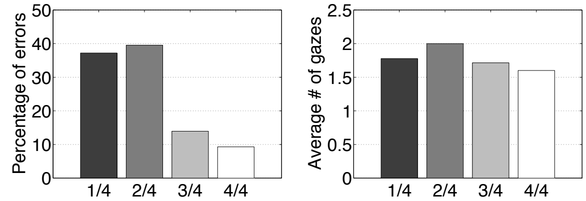


Figure 10: (Left) Distribution of error cases and (Right) average number of gazes before the subjects' response over the four quarters of the experiment duration.

subjects repositioned it before the unsuccessful action completes (Fig. 9(b)).

The moments at which the person takes their turn and interrupts the trial can *inform* the robot that the salient part of the effect has already occurred. For the first example the salient part is the lifting (the rising of the object in the visual field) rather than the dropping, and for the second example the salient part is when the arms are joined together in the front and start moving upwards without the object.

5.2 How can the robot influence the teacher?

Our second research question deals with the output from the robot to the human, investigating the effects of Junior's gazing behavior. We hypothesize that gazing will improve the interaction by informing the subjects about error situations, speeding up their response and inducing the correct response. We compare the gaze and no-gaze groups on the average time to respond to an error and the response given in an error case. Data from two subjects in which the error case occurred only once are excluded in this analysis.

Our data suggests that the robot is able to use gaze as a transparency device, communicating when and what it needs assistance with. Gaze improves the interaction by reducing the time for recovery from the error. We calculate recovery time by subtracting the individuals' average normal interaction time, from the time they take to respond to error cases, in order to reduce the effect of individual interaction speed differences. The average recovery time of subjects in the no gaze case is $13.57sec$ ($SD = 12.01$), whereas in the gaze case it is $11.69sec$ ($SD = 15.89$) which was not a significant difference, $t(95) = -0.65, p > .05$. However, our hypothesis holds for the majority of subjects (%92). When one outlier is removed from the gaze group the average recovery time the for the this group becomes $5.93sec$ ($SD = 11.27$) and the difference becomes significant, $t(72) = -2.58, p < .05$. We believe these results are due to the distractions and number of error cases in the outlier subject's experiment, future work will confirm these results.

In order to further investigate the influence of the gazing behavior on the teacher, we analyze the change of two measures over time after the first occurrence of gazing: average number of error occurrences and number of gazes before the human reacts. We find that both measures decrease in the second half of the experiment (Fig. 10). This suggests that people understand the error and get better at positioning the object so less errors occur. Alternatively, it could be that they learn that responding to the gazing by repositioning the object solves the problem, even if they don't exactly understand the problem. Either response leads to the desired outcome from the robot learner's perspective.

In the questionnaire, subjects were asked two questions about gazing: whether Junior ever gazed at them and in which situations it did so. The first question revealed that all the subjects in the gaze case noticed the gazing (even if it happened only once) and none of the subjects in the no-gaze case confused Junior's other head movements (during object tracking or random search) to be a gaze directed to themselves. This suggests the gazing behavior was noticeable and distinct. Accordingly, subjects in the gaze case saw the communication act and felt the need to respond in some way. The fact that subjects could appropriately respond to the gaze, even though they were not informed about the behavior prior to the experiment, confirms that gaze is a natural way to ask for assistance.

When error conditions occurred in the no-gaze case, subjects kept waiting for Junior to do something, and hesitated to move the object thinking it could start the action anytime. Two experiments in the no-gaze case were interrupted by the subjects asking for assistance, as nothing was happening, and the experimenter had to remind them that the objects need to be horizontally centered for Junior to act on them. This did not happen with any subjects in the gaze condition.

When people in the gaze group were asked, "In what situation did Junior gaze at you?" none could precisely identify the problem. They said that it happened when Junior couldn't see the object or when Junior was *confused*. This suggest that subjects were intuitively able to respond properly to solve the error without exactly knowing what it was.

Finally, we noticed that the robot could use the gaze behavior to *learn* the kinds of assistance it can get from the human partner, learning the causal relationship between a request for assistance and the response. In the no-gaze group it would be difficult to associate an error with a response given by the human. The time after which an individual will suspect an error can highly vary. On the other hand, responses can easily be associated with gazes. In this respect the robot could learn the effects of the gazing action *in a social context* in a similar way that it learns the effects of grasping

Figure 11: The effect of gazing: three frames from Junior's camera captured at the start, middle and end of the gaze, the effect of the gaze in this case is repositioning of the object such that it is centered.

and poking. In a sense, it could learn the affordances of the human teacher. For example, given a few perceptual experiences like the one seen in Fig. 11, one could imagine that the robot would learn that the effect of gazing at the human is that an un-centered object becomes centered.

5.3 What is the Machine Learning impact?

Our third research question addresses the effect of social versus non-social exploration on the underlying Machine Learning process. We hypothesize that humans are effective teachers, providing a compact data set that efficiently captures the various object affordances. We analyze a specific example of learning, using SVMs as affordance classifiers.

A two-class SVM is trained for each type of effect, using the state of the object as the feature space and the affordance (whether or not the action resulted in the corresponding effect) as the target value. Separate SVMs are trained with the social and non-social data sets, and test data sets are obtained by randomly sampling equal numbers of positive and negative examples from either the systematic or the social data set. Thus, learned classifiers are compared with two separate tests, one social and one systematic.

Fig. 12 compares the average successful prediction rate for classifiers with four different training data sets: (i) the complete set of examples collected systematically, (ii) 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) the data sets obtained by individual subjects in the experiment.

Our first observation is that the complete data sets (systematic and combination of everyone) generally perform better than the smaller data sets (random subsets and individuals). This shows that the number of samples given by one individual in a single sitting 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 having multiple teachers. Nonetheless, as observed through the error bars some individuals were able to get close to the performance of the complete data sets.

The social training sets perform better on rolling and opening affordances in both test cases. This is a result of the balanced nature of the data provided in the social case (Sec. 5.1.1). As these affordances are rare in the systematic data set, the non-social training 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 systematic training set or one is slightly better depending on the test set.

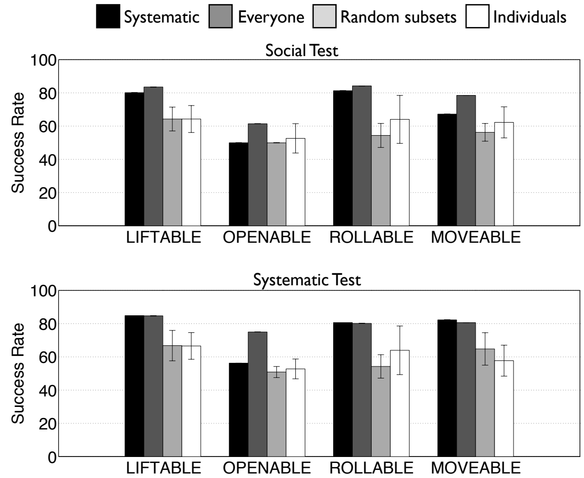


Figure 12: Learning results: Prediction success of classifiers trained with the systematic (non-social) data and the social data, on (Top) social test data and (Bottom) systematic test data. Values averaged over 10 randomly sampled test sets.

We believe this result is related to what people focus on during the experiment. While rolling and opening happen rarely in the systematic experiment, because of the way it was designed, they are obvious affordances to a person presented with spheres and a cylindrical box. Thus, they are successfully taught to the robot in the social case. This is a good example of how humans can indirectly transfer their knowledge about the world to the robot. It may be difficult for a robot to automatically devise an exploration strategy to cover the affordances of the environment in a balanced way, but humans can support robots by scaffolding the exploration, implicitly using their knowledge about the world.

Depending on the employed machine learning method, the differences in the data acquired socially and non-socially will impact learning differently. For example, an algorithm that is sensitive to data presentation order may give different results when presented samples structured by a human partner as opposed to a systematically or randomly ordered set. In our case, learning performance was altered by differences in the balance between positive/negative samples in the data, as well as the sizes of the data sets. In order to improve performance, a robot could use prior knowledge about characteristics of the data to apply different learning methods in social and non-social situations. Devising such adaptive learning methods is an interesting future challenge.

6. CONCLUSIONS

Our goal is to explore Socially Guided Machine Learning, viewing robot learning as an interaction between an embodied Machine Learner and an everyday human partner. In this paper we take the context of learning about objects with a human teacher. Using the Junior robot platform, we collect training data for SVM classifiers in two different settings: *Social*–the interaction is structured by a human partner; and *Non-social*–the robot is presented a systematic set of object configurations to explore.

This experiment makes three primary contributions. First we characterize the input from a human teacher in this object exploration setting. We have six observations about how the social data set differs from the non-social data set: People have a more balanced set of positive and negative examples. They intuitively structure the environment with respect to complexity, both in number of examples per object and order of examples. Social data sets have a greater representation of rare affordances. And people's actions in the workspace can be used to infer action goals.

Having analyzed the input portion of the learning process, our second contribution is in the output channels. With half of our human subjects, Junior used a gazing behavior to indicate errors. Our data suggests that Junior was successfully able to use gaze as a transparency device to communicate that it needed assistance, leading to faster error recovery.

Finally, our third contribution is in analyzing the impact that a socially collected training set has on a supervised learning mechanism. We trained SVM affordance classifiers with the social and non-social data sets. People provided small data sets, but they were focused and effective. The social SVMs were better at predicting rare affordances since people focused on these, and they performed on par with non-social SVMs on the more common affordances.

Robots operating in human environments will likely need to interact with everyday people to learn new things. Our research in SG-ML provides insight and guidance into how these systems should be designed to more appropriate match how everyday people approach the task of teaching.

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