Tests were conducted by providing permissions for either 100%, 75%, or 25% of the objects, and either a noiseless ownership condition (ownership relations were known with full certainty) or noisy ownership condition (ownership relations were known with 40% to 80% certainty). The accuracy and F1 measure of the induced rules were computed for each action, then averaged across the actions. The results are summarized in Table 1, along with the baseline performance when the system does no rule learning and simply assumes all actions are allowed.

Average rule accuracy / F1 measure			
Ownership relations	Fraction of permissions provided		
	1.00	0.50	0.25
Noiseless	0.995 / 0.995	0.945 / 0.875	0.787 / 0.523
Noisy	0.889 / 0.840	0.842 / 0.724	0.761 / 0.519
Baseline	0.583 / 0.000	0.583 / 0.000	0.583 / 0.000

Table 1: Performance metrics for norm learning

As can be seen from the results, the norm learning component was able to achieve reasonable levels of performance even under noisy, low-information conditions, with more than 76% of the permissions accurately predicted by the induced rules. When at least 50% of the permissions were provided, manual inspection of the induced rules in the noiseless condition revealed generally similar semantics to the actual rules. Under noisier or lower information conditions, the semantics of the induced rules tended to differ considerably. However, this is to expected, since there are many possible rules which cover a limited set of examples. Should semantically incorrect rules be learned, dual-mode instruction allows for human users to correct the robot by directly providing the actual rule. As such, in more realistic situations where the system receives a combination of object-specific permissions and direct rule instruction, its performance can be expected to be even better.

Ownership prediction and inference

Ownership prediction and inference were tested by sequentially providing both the true ownership relations and object-specific permissions for half of the objects at random, and then evaluating ownership accuracy for the other half. To investigate the effects of integrating rule induction and rule-based inference with percept-based prediction, three conditions were tested: (i) rule-based inference was disabled (so it did not matter if rules are provided); (ii) rules were learned from the permissions; (iii) rules were directly provided from the start. The same set of rules were used as in the norm learning experiment. The results are presented in Table 2

It can be seen from the results that the system achieves reasonably high levels of predictive performance despite the limited amount of training data. Enabling rule-based inference does not lead to an improvement in ownership prediction, because in this training scenario, ownership relations are provided along with permissions. However, in an alternate scenario where permissions but not relations are provided, our testing also shows that the correct relations are inferred from the rules (we omit these results because they follow from the correct implementation of Equation 1). More importantly, Table 2 shows that combining prediction with inference results in no significant reduction of accuracy. This is the case even when rules are induced instead of directly provided. All three conditions result in almost equal levels of performance. These results indicate that the three learning components are well integrated and do not come into conflict with each other.

Metric	Rule Learning / Inference		
	None / Off	Learn / On	Given / On
Accuracy	0.904	0.897	0.896
F1 measure	0.757	0.747	0.744

Table 2: Performance metrics for prediction and inference

Task-based evaluation

A holistic evaluation was performed by instructing the system to either collect or throw away all objects in the workspace, except where doing so would violate a set of norms it had to learn. The norms specified were the same as in prior experiments. Every time the system mistakenly tried to act or failed to act, it would be corrected by providing the true permissions. If ownership was relevant to the applicable rules, then the true owners were also provided. This feedback protocol standardizes how human instructors usually provide guidance. If no correction was needed, then the system would assume that the permission it had predicted was accurate, and add it as a example to the permissions database. Note that `pickUp` is a prerequisite to both `collect` and `trash`, so the rules for `pickUp` also had to be learned.

Task-based performance					
Task	No. of mistakes	Rule		Ownership	
		Acc.	F1	Acc.	F1
collectAll	6.30	0.975	0.937	0.344	0.273
trashAll	6.32	0.877	0.812	0.822	0.511

Table 3: Performance metrics for task-based evaluation

Results for this evaluation are presented in Table 3. As a measure for how smoothly the task was learned, the average number of mistakes made was recorded. The worst case is a mistake for all 20 objects. If the system were incapable of learning norms and instead assumed all actions were allowed, then the baseline number of mistakes would be 8.75 for the `collectAll` and 15 for the `trashAll`.

For both tasks, the system committed significantly fewer mistakes than these baselines. It was also able to learn the rules with high accuracy. In the case of `collectAll`, ownership information was only provided for agent 2's objects, because `forbid pickUp if ownedBy agent 2` was the only ownership-relevant norm applicable. This explains the low ownership accuracy for `collectAll`, compared to the high accuracy for `trashAll`. It should be noted that this performance was achieved by the system only after 20 examples, with no prior knowledge of the ownership norms or relations, nor any direct instruction of norms. These results thus attest to system's ability to learn rapidly and flexibly while performing useful tasks.

Video demonstration

To demonstrate the system's capabilities in the real world, we provide a video at the following URL: `https://bit.ly/2z8obET`. We demonstrate the system's capabilities on the Baxter robotics platform in three scenarios. Still frames from the first and second scenario are shown in Figure 1, while frames from the third scenario are shown in Figure 2. The first scenario shows the the system's ability to respond to the reprimand,"No Baxter, that's mine!" when it tries to throw away a red object after being asked to clear the workspace. The reprimand is simultaneously interpreted as direct instruction of a norm, an object-specific permission, as well as an ownership claim. The system then uses perceptual heuristics to generalize application of the norm, completing its task while avoiding touching any of the other red objects, which it correctly predicts to belong to the user.

The second scenario follows chronologically after the events of the first scenario, and shows the system's ability to represent owner-specific norms, as well as refuse to perform commands that violate the norms it has learned. When a new user appears and commands the system to throw away an object it believes to be owned by the first user, the system refuses and apologizes. However, when the new user claims exclusive ownership over that object, the norm specific to the first user no longer applies, and the system throws away the object when commanded to do so again. The third scenario shows the system's ability to induce norms from a series of object-specific permissions. It is initially aware of the ownership status of the blocks in the workspace, and uses that information to induce the norm that it should not pick up objects if they belong to someone.

Discussion

The system presented here is an initial foray into the complex challenges posed by norm learning in social environments. It addresses a subset of these problems by bringing together several distinct approaches to AI, demonstrating the utility of such integration. Firstly, it connects work in normative human-robot interaction to the literature on rule induction, showing how approaches inspired by traditional rule learning can induce condition-sensitive norms in social environments. Secondly, by deploying real-time probabilistic rule learning and evaluation, it shows how explicit and interpretable representations of normative criteria can achieve and even facilitate the dynamism and flexibility required for social interaction. Thirdly, it shows how rule-based approaches can be effectively integrated with both probabilistic reasoning (ownership inference) and sub-symbolic machine learning (percept-based heuristics) in a principled manner. As such it opens possibilities for the combination of relational reasoning, probabilistic cognition, and deep learning that may be necessary for human-level social competence (**?**; **?**).

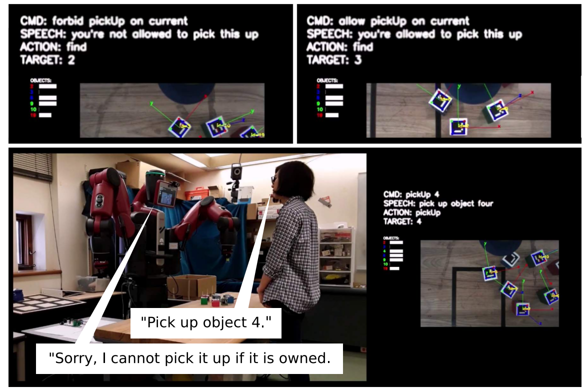

Figure 2: Norm induction from specific examples. *Top left*: The robot is forbidden from picking up object 2 (owned by Xuan). *Top right*: After two more examples of owned and forbidden objects, the robot is allowed to pick up object 3 (unowned). *Bottom*: The system generalizes these examples into a norm that forbids picking up any owned objects. When asked to pick up object 4 (owned by Xuan), it denies the request in accordance with the learned norm.

However, many other norm-relevant capabilities remain unexplored. We note that the current system can only learn norms that apply to its own actions. Future representational extensions should allow for agent-general norms, norms with temporal semantics (e.g. borrowing), and higher-level normative concepts such as ownership rights and duties (**?**). Another complexity is adjudicating between conflicting norms or goals, which might be addressed by integrating existing approaches to the problem (**?**; **?**). To increase the system's scope beyond a basic set of actions, predicates and heuristics, the system could employ one-shot learning of actions and objects (**?**), multi-modal semantic grounding (**?**), and automatic feature selection (**?**). The sources of normative information could also be expanded, allowing for the inference of norms from how agents interact with objects and other agents in the environment. While some ethicists and legislators have argued that robots should own themselves (**?**), much work remains before robots can understand the very concept of ownership.

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