Today the expertise required to design and deploy robotic systems exclude domain-experts who lack programming skills. My research vision involves developing computational models and algorithms that allow domain experts to directly train robots just as they would train a human apprentice. Specifically, they would enable users to convey complex task specifications through intuitive modalities like

Spoken? How is this delivered?

demonstrations, instructions or plan sketches; and robots to seek information from the user to reduce its own uncertainty over the intended task specification. These developments would democratize automation tools, thus contributing to the vision of pervasive agile and supportive automation deployed in the real world. Such technologies would enable everyday users to teach domestic robots to perform their household chores; factory workers to reprogram robots on the assembly line; and astronauts to flexibly deploy autonomous exploration vehicles.

Human apprentices learn by leveraging expert's demonstrations or instructions. Although these are ambiguous sources of information, the apprentice reconciles these ambiguities when asked to perform the task. On the other hand, given an opportunity to ask questions to the expert, the apprentice seeks to reduce their uncertainty arising from the ambiguities. My PhD research resulted in the first robotic system capable of such learning behavior by a robot in the context of complex temporal tasks. In doing so, I developed an interactive framework (Figure 1) that not only allows the user to teach a task through demonstrations [1, 2, 3], but also allows the robot to generate queries for the user that optimally reduce it's own ambiguity.

Is uncertainty the main technical hurdle?

In my future research program I would like to build on this foundation by enabling richer variety of training modalities, and developing methods for the robot to communicate it's learning back to the user. Finally I would also like to develop tools to explicitly characterize the complexity of tasks the robot can learn.

Current Research

Figure 1 depicts the interactive learning framework that I developed as a part of my PhD research. It allows the robot to assimilate ambiguous information provided by the expert into a belief over specifications. It also enables the robot to query the user for assessments to refine its own beliefs. During my PhD research, I lead the following research thrusts:

Encoding ambiguities in user provided demonstrations:

This easy to argue with. LTL is only as good as the model.

Formal languages like linear temporal logic (LTL) [4] are ideal to unambiguously define task specifications. However, they can be unwieldy for a domain-expert as compared to providing task demonstrations. To reconcile the ambiguity of demonstrations, I developed Bayesian specification inference [1], a probabilistic model to infer a belief over candidate LTL formulas that represent the user's intended task. The choice of LTL enabled the learning of non-Markov temporal tasks while a Bayesian approach captured the uncertainty of the model over the candidate task specifications.

I demonstrated that Bayesian specification inference correctly identifies – as the most likely candidate formula – the LTL formula representing the real-world task of setting a dinner table from as few as 50 demonstrations. We also applied this model for inferring mission objectives from simulated flight

Do you have better examples?

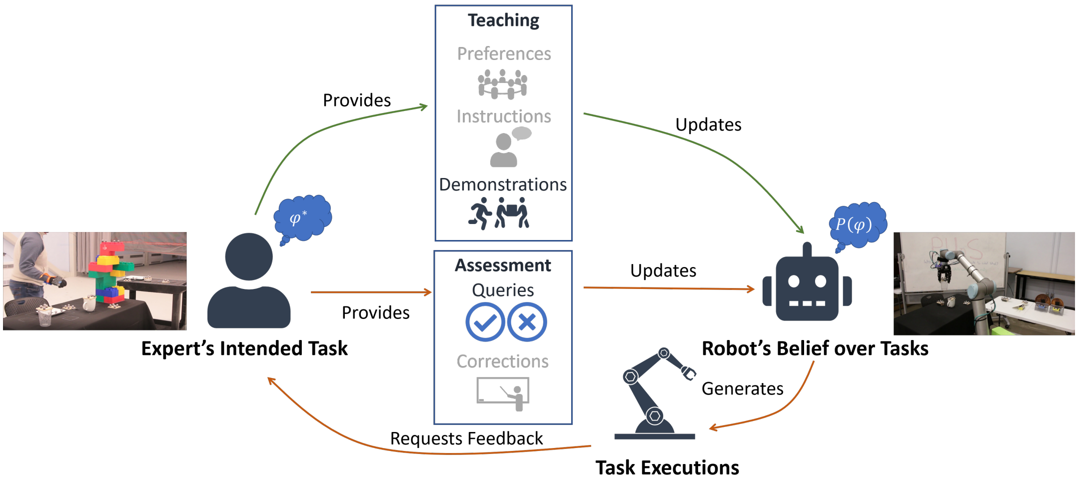

Figure 1: A unified framework for training a robot through multiple accessible modalities. The expert intends to teach a specific task φ^* to the robot. Meanwhile, the robot maintains a belief $P(\varphi)$ over candidate tasks that it must perform. 'Teaching' is the type of input that is initiated by the user, while 'Assessments' is the type of user input requested by the robot. I have primarily focused on demonstrations and queries as input modalities for my PhD research.

What is the ten year vision of problems that must be solved to make this a reality?

What was the baseline? Has anyone done this before?

missions with multiple aircrafts[2]. The inferred posterior beliefs over LTL formulas describing the mission objectives had over 95% agreement with the mission commander's assessment. The logical structure of the formulas, allowed the mission commander to interpret the model's reasoning in case of disagreements. These models are at the core of an automated mission analysis and review system that I helped in developing with my industry collaborators «IITSEC papers».

Formalizing decision-making with uncertain specifications:
Prior research into planning with LTL specifications has considered the task specifications to be known unambiguously. However, models like Bayesian specification inference challenge this assumption by maintaining a belief over task specifications. I developed planning with uncertain specifications (PUnS) [3], a novel planning formalism to allows robots to explicitly reason about its own uncertainty over task specifications. I defined four evaluation criteria that determine the extent to which a candidate task execution satisfies a belief over LTL formulas. I demonstrated that these evaluation criteria can be represented as non-Markov rewards and developed algorithms to compile these non-Markov problems into an equivalent and provably minimal Markov decision process (MDP).

What does it mean to satisfy a belief over specifications? A PAC bound?

The dinner table again is not a super-compelling example.

I demonstrated that optimizing for PUnS evaluation criteria allowed the robot to correctly set the dinner table using posteriors inferred from 30 demonstrations. The choice of the evaluation criterion resulted in a trade-off between creativity in task execution (unique placement orders executed by the robot) and risk aversion with respect to the learned specification. Inspite of the ground truth specification not being the most likely specification as per the belief, the robot's policy was estimated to have a low error rate of $10^{-6}\%$[1] (through simulations). Thus PUnS as a decision-making formalism allows reconciliation of ambiguity arising from expert's inputs.

What's the baseline?

Refining robot's belief through interaction: More to next pg.

1 - The video can be seen at `https://youtu.be/LrIh_jbnfmo`

Bayesian specification inference and PUnS can be used in conjunction with each other for a user to initialize the robot's belief using demonstrations as a teaching method. However, the robot can use the initial belief $P(\varphi \mid \{\boldsymbol{D}\})$ in conjunction with the MDP reformulation of PUnS to indentify a task execution trajectory whose acceptability is the most uncertain. The robot then demonstrates this query back to the user and elicits an assessment of that executions acceptability from the user. Next, BSI can be applied using the $P(\varphi \mid \{\boldsymbol{D}\})$ as the new prior. I developed models that allow the robot to determine what the most informative query would be.

Through simulation experiments, I confirmed that such an approach leads to a higher certainty (measured by the entropy of the belief distribution) and a better alignment of the belief with the ground truth specification as compared to learning purely from expert demonstrations. Empirically, we found that the active querying approach inferred the true specification with near certainty with eight data points, while the batch method struggled to achieve an equivalent level of similarity with as many as 50 demonstrations. We are currently performing a human-participant study to compare the user's subjective assessments of the system to the objective metrics. The framework I developed as a part of this study is the first active learning system for non-Markov tasks.

Future Research Agenda

My research so far has laid the foundation for an interactive training system that leverages demonstrations as a mode of communication between the teacher and the learner. In my future research program I plan to expand my formulation to include additional user input types for tasks for tasks of higher temporal complexity. Doing so would involve making advances in reinforcement learning, formal languages and probabilistic modeling. My next research thrusts would be as follows:

Not clear what this means

Enabling a variety of intuitive teaching modalities:
When human experts train apprentices, they do not limit themselves to purely demonstrating their craft and determining the acceptability of their apprentice's efforts. They utilize all modalities available to them, for example, natural language instructions, explanations, preferences. Further more, when critiquing an apprentice's efforts, they also provide rationale for their criticisms along with suggested corrections. Every form of teacher input is as an attempt to modify the learner's belief over task specification. The PUnS and the Bayesian specification inference formalism provide a unifying framework for modeling the teacher's input. In my future research, I plan to further the understanding of the relationship between natural and formal languages to leverage natural language interactions for teaching and assessing the robot. I also plan to explore the role of pragmatics in appropriately generalizing information gained from the teacher's corrections.

Not clear why this is hard. What's your theory of the case?

✓ Pragmatics good!

Enabling the user to assess the robot's belief:
The demonstration of their skills are not the only way for a human expert to evaluate their apprentice's learning. Similarly, The PUnS formulation and the induced robot policy enables a richer evaluation of the robot's decision-making than just demonstrations.

I couldn't tell what this sentence means.

I am especially interested in leveraging the advances in explainable AI systems and probabilistic programming languages to allow the user to explore the robot's policy through counterfactual queries. I am also interested in developing interpretable representations of the underlying belief that can be directly assessed by the user. Such assessments of the robot's underlying belief and policy can reveal spurious correlations inferred by the robot or reveal regions of state-space with inadequate exploration during training.

This is good but a grab bag of stuff. How does your experience apply here? How will you plan to make progress?

Most readers will not know what this is. Too much 'jargon'.

Enabling tasks of higher complexity:
The PUnS formulation allowed the robot to generate plans to satisfy temporal properties that belong to the 'Obligation' class of Manna and Pnueli's [5] temporal hierarchy. While this is an advance from the previous state-of-the-art, this class does not encompass a wide variety of tasks, for example: reactive and recurring tasks; or tasks with non-deterministic outcomes. In my future research, I would like to develop a formal specification language for robotics to enable explicit characterization of tasks that the robot can learn and work towards expanding that repertoire of tasks. In parallel, I will to develop algorithms for automatic compilation of these complex task into problem formulations suitable for automatic planning.

Not interpretable by the general computer scientist.

Summary

Advances in autonomous systems, robotics and artificial intelligence have a great potential to enhance our future lives. My vision is to empower domain-experts who may not have programming skills to participate in the development of these technologies. My future research program provides a roadmap for key enabling technologies that contribute to this vision.

My research has broader applications beyond robotics including decision support systems in aerospace applications, healthcare and emergency response. I will continue pursuing collaborations with the industry to deploy mature technologies from my research program into the real-world.

[1] - A. Shah, P. Kamath, S. Li, and J. Shah, "Bayesian inference of temporal task specifications from demonstrations," in *Conference on Neural Information Processing Systems*, 2018
[2] - A. Shah, P. Kamath, S. Li, P. Craven, K. Landers, K. Oden, and J. Shah, "Supervised bayesian specification inference from demonstrations," in *(under review)*, 2019
[3] - A. Shah, S. Li, and J. Shah, "Planning with uncertain specifications (puns)," *arXiv preprint arXiv:1906.03218*, 2019
[4] - A. Pnueli, "The temporal logic of programs," in *Foundations of Computer Science, 1977., 18th Annual Symposium on*, pp. 46–57, IEEE, 1977
[5] - Z. Manna and A. Pnueli, "A hierarchy of temporal properties (invited paper)," in *Proceedings of the ninth annual ACM symposium on Principles of distributed computing*, pp. 377–410, 1989