# Self-assessing and Communicating Manipulation Proficiency Through Active Uncertainty Characterization

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***Abstract*—Autonomous manipulation has the potential to improve the quality of life of many by assisting in routine household tasks such as cooking, cleaning, and organizing. However, for safe, dependable, and effective operation alongside humans, both the robot and the human must have an accurate and reliable assessment of the robot's proficiency at completing the relevant tasks. Such an assessment helps to ensure that the robot does not engage in tasks that it cannot handle and instead engages in tasks that are well-aligned with the robot's abilities. This proposal thus investigates how a robot can actively assess both its proficiency and its confidence in that assessment through appropriate measures of uncertainty that can be efficiently and effectively communicated to a human. The experiments examine how a user's trust and subsequent use of a robot vary as a result of the robot's self-assessment of proficiency.**

***Index Terms*—Trust Alignment; Proficiency; Confidence; Uncertainty; Introspection**

## I. Introduction

Due to the high dimensionality of manipulators and the difficulty of modeling contact physics, learning has thus emerged as a major paradigm for robotic manipulation. While much of the recent literature has focused on attaining a variety of skills such as pushing [1], scooping [2], and pouring [3], accurate and reliable characterization of the robot's resulting proficiency across a variety of environments is necessary before robots transition out of controlled laboratories into everyday environments such as homes.

In this proposal we aim to answer the following question: *Given a pretrained manipulation policy, how should a robot assess its proficiency across a range of environmental conditions to develop a shared understanding with a human?* The proposed research is guided by the following three principles:

1) Uncertainty is pervasive in robotics due to noisy sensors and actuators, approximate models, and incomplete information. For informed decision making, it is important to not only estimate the quantity of uncertainty but to also understand the constituent types and causes. The first thrust will thus aim to both identify and quantify the uncertainties associated with the estimated proficiency for a given task.

2) A calibrated understanding of the robot's proficiency is critical to effective collaboration between a human and a robot. If the human under-trusts the robot, he or she may fail to fully utilize all of the robot's capabilities. On the other extreme, the human may over-trust the robot, which may lead to unrealistic expectations and potentially dangerous consequences [4, 5]. The second thrust will thus actively learn and convey the critical boundaries of the state space that straddle where the robot can and cannot be trusted reliably.

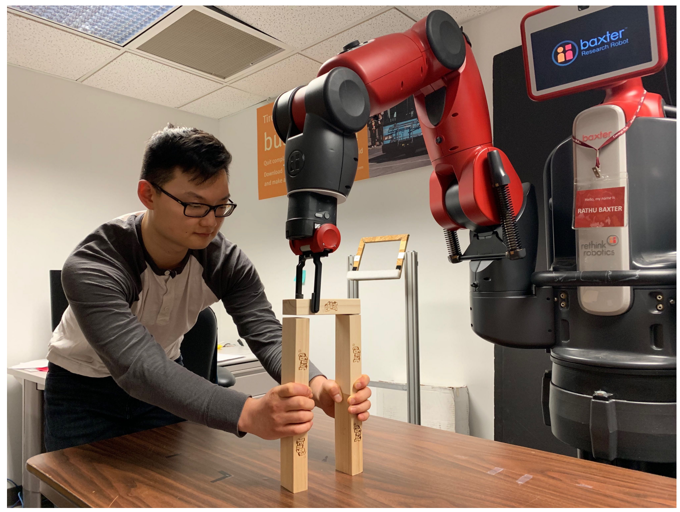


Fig. 1. An accurate assessment of a robot's proficiency is critical to a well-calibrated user trust and effective collaboration. Above: Recognizing that the blocks comprising the two columns aren't secured to one another, the user secures them with his hands and relies on the robot's proficiency at placing blocks onto a stable platform to finish the arch.

3) When conveying the results of the self-assessment, the robot should not provide an explanation that is too detailed nor too abstract, which will deter the efficiency and effectiveness of the communication. This final thrust will thus determine the primary variables contributing to the high uncertainty through sensitivity analysis of the states that comprise the resolved boundaries in the state space.

## II. Problem Definition

Key definitions for the proposed work are as follows:

**State space:** As the pretrained manipulation policy will remain fixed, the state space will be defined over relevant environment variables. For example, for block manipulation tasks the state space could be over the number, locations, mass, and coefficient of friction of the blocks.

**Proficiency:** For a domain $M$ comprised of states $\mu \in M$, assume that a policy $\pi$ on a state $\mu$ yields the measurement $R(\pi, \mu)$. A common performance measurement of policy $\pi$ over a domain $M$ is the average-case performance, which is defined as $\phi(\pi, M, p) = \sum_{\mu} p(\mu) \cdot \mathbb{E}[R(\pi, \mu)]$ where $p(\mu)$ is the

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probability of that state occurring [6]. In the equation above, an expectation is taken over $R$ as the measurement may be stochastic.

In this proposal, the measurement is $R(\pi, \mu)$ is assumed to be a measure of task success or failure captured by the indicator function $\mathbb{1}_{\Omega}(\pi(\mu))$ that denotes whether the result of running the policy $\pi$ on state $\mu$ is or is not in the set of successful states $\Omega$. Thus, $\mathbb{E}[R(\pi, \mu)] = \mathbb{E}[\mathbb{1}_{\Omega}(\pi(\mu))] = p\Big(\pi(\mu) \in \Omega\Big)$ is termed proficiency (i.e. the probability of task success using policy $\pi$ in the state $\mu$).

**Confidence in proficiency:** With proficiency defined as the probability of task success, the confidence in the proficiency assessment can consequently be captured by the corresponding variance (i.e. uncertainty) of that probability.

## III. Research Overview

*1) Uncertainty Characterization: How certain should the robot be about its proficiency and why?* One useful categorization of uncertainty that has reemerged in the machine learning community is epistemic and aleatoric uncertainty. Epistemic uncertainty arises from a suboptimal model given a set of input variables, and can theoretically be reduced as more data is observed. On the other hand, aleatoric uncertainty arises from unmodeled variables and cannot be reduced even with more data [7]. Epistemic and aleatoric uncertainties indicate to a human which uncertainties can be reduced by further training and which cannot, providing a better understanding of the current and future limitations of the learned policy.

If the proficiency assessment module is represented as a network, then epistemic uncertainty can be estimated using Monte Carlo dropout by placing a Bernoulli distribution over the network weights. Aleatoric uncertainty can then be estimated with a modified loss function with an extra variance term [8]. To capture epistemic and aleatoric uncertainties within a Gaussian Process (GP) instead, appropriate variance terms may be added to the kernel function [9].

*2) Trust Region Discrimination: In which regions of the state space can the proficiency assessment be trusted?* A relevant field in manipulation is called precondition learning, which aims to learn the environmental conditions in which a learned skill is applicable. Recent work on precondition learning include learning relevant preconditions as features that exhibit little variation in value before demonstrations [10] and using a random forest to learn how object shapes and sizes affect tasks such as placing, pushing, tilting pouring, cutting, and wiping [11]. However both of these learn the preconditions in a passive manner over provided demonstrations.

This proposal will instead aim to learn the preconditions in an active manner. Of specific interest are the boundaries within the space of possible preconditions that divide those that map to a proficiency measure with high certainty from those that map with low certainty. Following [12], a GP could be used to model this boundary, using straddle heuristic to actively sample preconditions near the boundary or where the epistemic and aleatoric uncertainties are high. This boundary would provide a compact representation of the key states to be aware of in assessing the robot's proficiency.

*3) Variable Relevance Discrimination: Which environmental variables are critical to the proficiency of this task?* The final research thrust of this proposal considers the discrimination of the environmental variables that are critical to the robot's proficiency and its self-assessment. One major thrust in recent explainable AI is sensitivity analysis, which analyzes the sensitivity of the performance with respect to changes in the input [13]. For example, sensitivity analysis has been used to explain image classification decision by determining which regions of the image lead to the greatest change in prediction score when perturbed [14]. With new advances in computation and in the fidelity of physics engines [15], sensitivity analysis will be performed in simulation.

However, performing sensitivity analysis exhaustively over the state space will likely be intractable. It has recently been proposed that in many tasks, the essence of a policy can be described by actions taken in a few critical states [16]. For example, the aggressiveness of an autonomous car's policy can be better captured by a few key interactions with other cars (e.g. does it yield to a merging car?) than many instances driving alone. Thus, sensitivity analysis will only be performed on states along the boundary discovered in the previous section.

## IV. Experimental Outline

The experiments proposed in this work will study how a robot's self-assessment of proficiency may aid in calibrating a user's trust. While a single definition and model of trust has yet to be broadly accepted by the research community, researchers have extensively studied the relationship between machine reliability and use without directly modeling the intermediate variable of trust [17]. This study will therefore also focus on how the variable of machine proficiency impacts the use of the robot system and the user's own assessment of trust.

Specifically, we will consider proficiency within the context of block manipulation. This domain includes tasks such as the construction of structures such as towers, as well as knocking down said structures such that the blocks fall in a particular direction (tasks common to the literature exploring intuitive physics [18–20]). The parameters of the blocks (e.g. shape, size, mass, friction coefficient) and the complexity of the structures (height, stability, etc) will be changed to vary the levels of stochasticity and complexity. Each task will be assigned a certain reward when completed by the human (lower) or the robot (higher), and the human must decide which tasks to entrust to the robot in order to maximize the overall score. Relevant skills will be trained on a Baxter robot using a pre-existing state-of-the-art reinforcement learning algorithm such as Guided Policy Search [21] or imitation learning algorithm such as CLAMP [22].

As noted earlier in the paper, it is critical to calibrate trust appropriately to prevent under- and overtrusting the robot. In this work, a well-calibrated trust will be represented by a 'rational' user whose use of the robot scales proportionally to the expected reward for using the robot given the user's perceived and robot's self-assessment of proficiency [23]. More frequent use of the robot in comparison will correspond to overtrust, and vice versa. How the robot's self-assessment of proficiency changes a) the subjective self-assessment of a user's trust toward the robot (measured using a Likert scale) and b) the frequency of robot use will be studied.

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