An Active Learning Approach for Embodied Concept Learning

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I. Introduction

In many natural settings training data is gained interactively, by taking actions, making queries, or performing experiments. In such a situation agent's most powerful tool is its ability to act, to gather data, and to influence the world it is trying to understand [1]. Most of research on active learning relies on black-box approach by assuming free-of-cost availability of required training data through a query, e.g., [13], [14]. An embodied agent, however, has to consider many aspects such as sensori-motor capabilities, ability to design experiments to generate required training examples, cost of such *interventional experiments*, and so on. Such characteristics of real world demand a careful analysis of otherwise theoretically near-optimal active learning algorithms.

Research on active learning for embodied agent has recently received more attention. Most of this work deals with sensory-motor learning such as learning forward model [2], [3], [4] or autonomous exploration, e.g., importance resampling for simultaneous localization and mapping (SLAM)[5]. On a higher level of abstraction, several discovery systems have exploited active learning for improving domain knowledge for planning [6], [7], [8]. Except a recent experimentation strategy for learning qualitative models through sensory motor exploration [9] , there is hardly any research work in field of active concept learning by an embodied agent.

To address open ended concept leanring by an autonomous robot, EU project XPERO [1] aims to develop an embodied cognitive system, which is able to conduct experiments in the real world with the purpose of gaining new knowledge about the world and to develop and improve its own cognitive skills and overall performance. XPERO provides an ideal environment for robotic discovery by defining several real world scenarios. The underlying learning challenges, for the robot, range from learning ego-motion from sensorimotor data to learning high level concepts such as movability of light-weight boxes as result of its action. The robot not only learns qualitative and quantitative laws but also gains new *insight* which enables it to simplify its theory about environment [10], [11], [9]. Gaining insight, requires that learned concepts be *interpretable* - this rules out many otherwise established machine learning schemes such as neural networks and support vector machines.

[1]More information can be found at www.xpero.org

In this work, we investigate several active learning approaches on a real world scenario and present an emerging approach for cost-effective active concept learning in physical world. The approach exploits different query selection criteria such as learning progress[2], low confidence[13], and exploration.

II. A Scenario for Embodied Concept Learning

For analysis of our proposed approach we chose the Bouncing Ball scenario, from XPERO, which consists of a robot, a ball, and a wall. The robot's initial model about the environment predicts that when the ball is pushed towards the wall, distance of the ball to the wall decreases up to a certain point (determined by its velocity and physical model of environment, e.g. friction) and the angle of the ball to the wall remains constant. However soon, this prediction fails, for example when the ball is pushed from near the wall with a high velocity. In cases like these, the actual outcome, i.e., bouncing of the ball from the wall shows an unexpected behavior of the world. This invokes improvement of model through active learning. Figure 1 shows two cases *without* and *with* prediction failure.

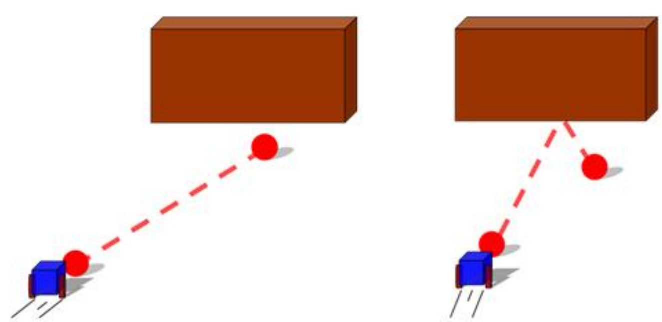

Fig. 1. On the left side, the robot pushes a ball which rolls until it naturally comes to rest (due to friction) without hitting the wall. On the right side, when pushed towards the wall the ball bounces back after hitting the wall.

The underlying concept learning problem can be modeled through different model types such as decision trees, neural networks, and predicates. For reason interpretability, we chose classification trees. Although classification trees are highly interpretable, they are unstable models [16], i.e., a small change in training data may result in a very different model. So the active learner can not exploit structure of the model for instance selection.

III. Previous Work

The simple schemes such as uncertainty sampling [12] which focus on instances closest to decision boundary of the model not only lack generality but are also infeasible for the unstable model types such as decision trees. Query by committee (QBC) approaches [13], [15] have shown significant results for classification as well as for regression. These approaches assumes that initial hypotheses are significantly different from each other. Most of active learning algorithms, including those discussed earlier, follow similar instance selection strategy, i.e., select instances from regions where learner performs poorly. This uncertainty is not the ultimate measure of importance and agent may stuck into too difficult situations or too easy situations [2]. To cope with that [2] presents intelligent adaptive curiosity (IAC), an active learning scheme for learning forward models, which enables a robot to systemetically explore regions of progressive complexity.

The main idea of IAC is to divide experimentation space in region and keeping track of agent's performance in each region through a so called measure learning progress (LP) on the regression task. IAC is intuitive to autonomous experimentation but its application to embodied concept learning is subject to several constraints including: (i) the prediction errors in concept learning are either 1 or 0 and not continuous values, (ii) we can not afford a large history window size in the given circumstances, and (iii) we can not afford a separate prediction model for each region. Thus evaluation of so called LP measure with discrete error values and small window size do not leave much room to distinguish the regions.

IV. The Approach

To cope with above issues, we first devise an enhanced criteria for evaluation of regions which not only consider absolute difference of recent and old errors but also take into account the variation within these sets as well as if a region has previously contributed in learning the concept. To choose expectedly most informative instance within selected region, we exploit query by committee approach. The proposed hybrid scheme first divides experimentation space in uniform regions and after performing some initial experiments build a committee of models for global space. Then active learning loop continues to select select a region and query instance. The region is selected using enhanced learning progress measure, whereas candidate instance within a region is selected for experimentation if the committee disagree on the prediction.

The algorithm along with the newly defined learning progress measure applies several query selection criteria in parall. These include: selecting regions of optimal learning progress, selecting regions with low confidence, selecting regions where less experiments are carried out and selecting regions which have high entropy. We implemented several strategies for the Bouncing Ball scenario and found promising results of the hybrid approach in comparison to random strategy, query by committee, and IAC-CL - a naive implementation of IAC to concept learning. With hybrid and IAC-CL approaches, we were able to show that the robot exhibits adaptive behavior by progressively experimenting regions of increasing complexity.

Acknowledgment

The work described in this paper has been funded by the European Commission's Sixth Framework Programme under contract no. 029427 as part of the Specific Targeted Research Project XPERO ("Robotic Learning by Experimentation").

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