An architecture for robotic discovery and learning by experimentation

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I. Motivation

Enabling machines to autonomously learn how to deal with novel situations, and to generalize the acquired knowledge in order to apply it to different situations, is a major challenge on the way towards building intelligent autonomous robots. In the past years, a number of approaches have attempted to learn relational knowledge that is general enough to be applied to different domains and contexts [2, 11, 8]. What is however still missing is a general architecture in which autonomous robotic learning for usage in everyday environments can be structured well [6].

In pursuit of enabling truly autonomous robotic learning, the work in the XPERO project [1] set out to design computational methods and mechanisms which enable an embodied intelligent agent (robot) to learn naïve physics concepts such as the geometry of motion or articulation only from real-world perceptions in a fully unsupervised way. By promoting the paradigm of *Learning by Experimentation*, this approach significantly differs from other implementations of Robotic Discovery and Experimentation such as [16, 1, 12]. Instead, *Learning by Experimentation* aims at enabling the agent to learn incrementally in an ”evolution of theories”. It should develop new theories and gain new insights by systematically investigating unknown phenomena and discovering regularities in the observed data. Depending on the observed phenomenon the new theory might be a revision of an existing theory or be built upon existing theories.

Learning by experimentation is a discovery process involving a sequence of steps, which finally terminate in the generation of a new or revised theory. The process is triggered by a failure to predict and explain a phenomenon that has been observed during the execution of everyday activities.

In XPERO, inductive learning paradigms such as ILP (inductive logic programming) [7], qualitative model tree learning [15] or learning of qualitative differential equations or partial derivatives [14, 13] were used to infer new concepts from real-world perceptions of naïve physical phenomena. Inductive learning paradigms are not particularly new research fields in machine learning. What is a rather unexplored field in machine learning is inductively learning new concept from the sensory data of a robot in order to improve and increase its understanding of naïve physical phenomena. One important challenge with using these learning techniques in robotics is obtaining meaningful and comprehensive data sets to trigger the learning process, after having observed a phenomenon the first time. In the following, we present the general architecture developed in XPERO for autonomous robotic Learning by Experimentation.

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

II. Three Behavioural Loops in Robotic Discovery

One important question when designing an agent that should learn *and* interact with the environment is how to initiate the learning process. In learning by experimentation, this is the question “What stimulates a robot to conduct experiments?”

We assume that our robot has in the past acquired a certain amount of knowledge which allows it to perform meaningful tasks. While doing so, it uses its knowledge to plan its actions and to predict their outcomes. If the robots predictions are consistent with observed consequences of its actions then apparently the robots knowledge is comprehensive enough to understand and explain the surrounding world. Occasionally the robot, however, will make an observation, which is inconsistent with its model of the world [4, 9]. We use such prediction failures as a trigger to investigate the observed phenomenon. This investigation involves steps such as forming some first educated guesses regarding the physical quantities, which might be relevant to model the phenomenon, designing experiments, collecting data, refining the educated guesses and eventually understanding the regularities behind the observed phenomenon [3].

For switching between learning and task execution, we propose an architecture supporting three operational contexts for the robot. Figure 1 shows these contexts and the three behavioural loops in which the robot might operate.

While the first loop models the robot’s everyday behaviour, the second and the third loop actually model the learning by experimentation process. In the following we describe these loops in somewhat more detail.

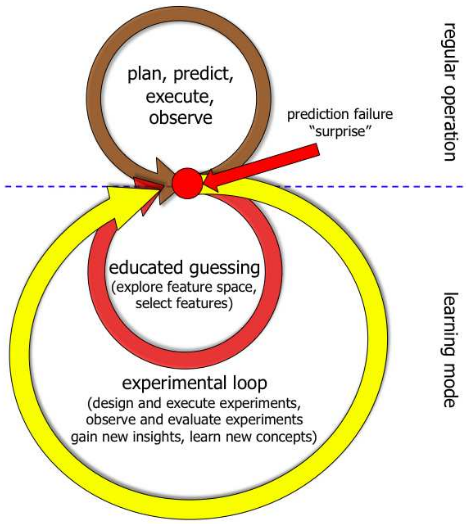

Fig. 1. Three Behavioural Loops in Robotic Discovery

A. The plan, predict, execute, observe loop

Using its innate planning and perceptual skills and available knowledge the robot can create and execute simple plans and perform simple tasks. While doing so, the robot will match its observations with what it already knows about the world. As long as the robot observes only ”known” things and as long as its predictions match its observations, the robot will remain in this loop since there is actually nothing ”new” to learn. If the robot, however, observes something which it cannot predict from its current knowledge, a switch to the learning mode is triggered, and the robot enters the educated guessing loop.

B. The educated guessing loop

One major purpose of the experimental loop is to collect a set of meaningful data from which the learning algorithms can infer a revised, refined or even a new theory. In order to guide this data collection process effectively, at the entry point of this loop we formulate an *educated guess* [5]. This educated guess identifies the physical quantities which may have contributed to the observed phenomenon and thus might be part of a theory explaining the phenomenon. An educated guess is mainly a subset of the power set of features, which might be directly extracted or constructed from the robot's sensor data. Hence we denote this operation also as *feature selection* in accordance with the standard Machine Learning terminology. Additionally, to guide the design of experiments, those ranges of feature values are specified which appear as relevant for explaining the observed phenomenon.

C. The experimental loop

The ultimate objective of the experimental loop is to gain insights about an unknown phenomenon and to learn new concepts. For this purpose the robot designs and executes a series of experiments to create meaningful data sets for the features sets specified in the previous step as educated guesses. These data sets should contain a sufficient number of (uniformly distributed) samples within the ranges specified in the educated guesses [10]. The data sets that result from the design, execution, and observation of these experiments are then forwarded to a learning component to induce a refined theory or model, which best explains the data and the observed phenomenon underlying these data. Ideally the learning component, which is involved in this loop, will be able to generate from these data one single and robust theory, which explains the underlying phenomenon.

III. RESULTS

The proposed architecture was implemented and tested with different embodiments, among others a Nao robot, in a simple real world environment for learning naive physics concepts. While very basic concepts such as the movability of objects could be learned, we still see a great need for generalization and extension of the framework.

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REFERENCES

[1] P.C-H. Cheng, *Modelling experiments in scientific discovery*, In Proc. of the 12th Int. Joint Conference on Artificial Intelligence. Sydney, Australia, 1991. Morgan Kaufmann, pp. 739-745, 1991.

[2] S. Hart, R. Grupen, D. Jensen, *A relational representation for procedural task knowledge*, In Proc. of National Conf. on Artifical Intelligence, vol. 20, no. 3, pp. 1280, 2005.

[3] T. Henne, A. Juarez, M. Reggiani, E. Prassler, *Towards Autonomous Design of Experiments for Robots*, In Proc. of CogRob workshop at ECAI2008, 2008.

[4] A. Juarez, A. Mohan, T. Henne and Erwin Prassler, *Qualitative Prediction-Observation: A Computational Model for Robotic Surprise*, In Proc. Int. Conf. on Cognitive Systems CogSys 2008, 2008.

[5] A. Juarez, T. Henne, B. Kahl, M. Reggiani, E. Prassler, *First Steps in Building a Framework for Learning by Experimentation*, In Proc. of IROS 2008 workshop on Robotic Challenges for Machine Learning II, 2008.

[6] P Langley, *Cognitive architectures and general intelligent systems*, AI Magazine, 27(2), pp.33-44, 2006.

[7] G. Leban, J. Žabkar and I. Bratko, *An experiment in robot discovery with ILP*, In Proc. of 18th Int. Conf. on Inductive Logic Programming, 2008.

[8] J. Modayil and B. Kuipers, *Autonomous development of a grounded object ontology by a learning robot*, In Proc. of National Conf. on Artifical Intelligence, vol. 22, no. 2, pp. 1095, 2007.

[9] A. Mohan, A. Juarez and T. Henne, *Q-POLE: A Qualitative Prediction-Observation loop for learning by experimentation*, In Proc. of Eurosim 2007, 2007.

[10] F. di Palma and M. Reggiani, *Design of Experiment for Qualitative Equation Discovery: a Comparison*, In Proc. of Eurosim 2007, 2007.

[11] H. Pasula, L.S. Zettlemoyer, L. Kaelbling, *Learning probabilistic relational planning rules*, In Proc. of the 14th Int. Conf. on Automated Planning and Scheduling, 2004.

[12] W.M. Shen, *The Process of Discovery*, Found. of Science, 1(2), 1995.

[13] J. Žabkar, I. Bratko, and J. Demšar, *Learning Qualitative Models through Partial Derivatives by Pade*, In Proc. of 21st Annual Workshop on Qualitative Reasoning QR'07, 2007.

[14] J. Žabkar, A. Sadikov, I. Bratko, and J. Demšar, *Qualitatively Constrained Equation Discovery*, In Proc. of 21st Annual Workshop on Qualitative Reasoning QR'07, 2007.

[15] J. Žabkar, I. Bratko and A. C Mohan, *Learning Qualitative Models by an Autonomous Robot*, Submitted to QR08, 2008.

[16] J. M. Żytkow, *Integration of knowledge and method in real-world discovery*, SIGART Bulletin 2(4), 1991.