Representation learning for acting and planning:  
A top down approach

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Short tutorial to be given at IJCAI 2022 (also at ICAPS 2022 but online); 1/4 day, 1:45h.

Description: In bottom-up approaches to representation learning, the learned representations are those that emerge in a deep neural net after training. In top-down approaches, representations are learned over a domain-independent language with a known structure and semantics, whether by deep learning or any other method. There is a clean distinction between what representations need to be learned (e.g., in order to generalize), and how such representations are to be learned. The setting of action and planning provides a rich, challenging, and crisp context for representation learning where three central problems are: 1) learning representations of dynamics that generalize, 2) learning policies that are general and apply to many instances, and 3) learning the common subgoal structure of problems; what in reinforcement learning are called intrinsic rewards. In the tutorial, we will look at languages developed to support these representations, methods developed for learning such representations, and challenges ahead.

Potential audience and prerequisite knowledge: Students and researchers interested in representation learning in the setting of actions and planning. Basic knowledge of AI, including logic and planning, assumed.


Tutorial outline

PART 1. Introduction: Learning representations over domain-independent languages

- Bottom up vs. top down approaches to representation learning
- Goals and scope of the tutorial
Part II. Languages for representing general dynamics, policies, subgoals

- Representing general dynamics: Lifted STRIPS, PDDL, SAS+, Action Languages, Structured Causal Models
- Representing general subgoal structures: Macro tables, HTNs, sketches; problem and sketch width, problem width and general policies

Part III: Learning language-based representations of dynamics, policies, subgoals

- Learning general dynamics
- Learning general policies
- Learning subgoal structures
- Combinatorial vs. deep learning approaches

Part IV: Wrap up, Future, Challenges

- The 3D Matrix: tasks, learning/optimization methods, state representations
- Grounded vs. ungrounded representations
- Visual languages
- Continuous domains, spaces, time, actions
- Stochastic and non-deterministic domains
- Extended temporal goals and rewards

Blai Bonet: Blai is a professor in the computer science department at Universidad Simon Bolivar, Venezuela. He received his Ph.D. degree in computer science in 2004 from the University of California, Los Angeles. His research interests are in the areas of automated planning, heuristic search and knowledge representation. He has received several best paper awards or honorable mentions, including the 2009 and 2014 ICAPS Influential Paper Awards, and he is a co-author of the book "A Concise Introduction to Models and Methods for Automated Planning". Dr. Bonet has served as associate editor of Artificial Intelligence and the Journal of Artificial Intelligence Research, conference co-chair of ICAPS-12, program co-chair of AAAI-15, and has been a member of the Executive Council for ICAPS and AAAI.
Hector Geffner: Hector got his Ph.D at UCLA with a dissertation that was co-winner of the 1990 ACM Dissertation Award. He then worked as at the IBM T.J. Watson Research Center in NY, USA and at the Universidad Simon Bolivar, in Caracas, Venezuela. Since 2001, he is a researcher at ICREA and a professor at the Universitat Pompeu Fabra, Barcelona, and since 2019, a Wallenberg Guest Professor at Linköping University, Sweden. Hector is a Fellow of AAAI and EurAI, and author of the books “Default Reasoning: Causal and Conditional Theories” , MIT Press, 1992, and ”A Concise Introduction to Models and Methods for Automated Planning” 2013, this one with Blai Bonet. He is also an editor of the books “Heuristics, Probability, and Causality: a Tribute to Judea Pearl”, 2010, and “Probabilistic and Causal Inference: The Works of Judea Pearl”, 2022, both with Rina Dechter and Joe Halpern. Hector leads a research project on representation learning for planning (RLeap), funded by an Advanced ERC grant (2020–2025), and still recruiting PhD students and postdocs.