ward maximizing long-term rewards.

Planning with POMDPs: POMDPs have been applied to a variety of probabilistic planning tasks (Young et al. 2013; Zhang, Sridharan, and Washington 2013). However, existing POMDP-based planning work does not readily support representation of or reasoning with rich commonsense knowledge. Furthermore, from a practical perspective, the state variables modeled by POMDPs have to be limited to allow real-time operation. This makes it challenging to use POMDPs in large, complex state-action spaces, even if hierarchical decomposition and approximate algorithms have been applied (Zhang, Sridharan, and Washington 2013; Kurniawati, Hsu, and Lee 2008).

The illustrative example problem in this paper is a Spoken dialog system (SDS). POMDP-based SDSs have been shown to be more robust and efficient than traditional work using deterministic flowchart-based action policies (Roy, Pineau, and Thrun 2000). A recent paper reviews existing techniques and applications of POMDP-based SDSs (Young et al. 2013). Similar to other POMDP-based applications, such SDSs are ill-equipped to represent and reason with commonsense knowledge.

Combining ASP with POMDPs: Existing work investigated generating priors by inference with domain knowledge using ASP for POMDP-based planning (Zhang, Sridharan, and Bao 2012). However, this work did not have a probabilistic reasoner to reason with probabilistic commonsense knowledge. Furthermore, the logical reasoner in that work did not calculate possible worlds for POMDPs. An action language has been combined with POMDP-based planning toward reasoning with qualitative and quantitative domain descriptions (Zhang et al. 2014a). The use of the action language limits the capability of reasoning with commonsense knowledge in that work.

6 Conclusions and Future Work

This paper presents the CORPP algorithm that, for the first time, integrates reasoning with (logical and probabilistic) commonsense knowledge and planning under probabilistic uncertainty. Answer Set Programming, a non-monotonic logic programming language, is used to reason with *logical* commonsense knowledge. P-log, a probabilistic extension of ASP, further enables reasoning with *probabilistic* commonsense knowledge. POMDPs are used to plan under uncertainty toward maximizing long-term rewards. The complementary features of ASP and POMDPs ensure efficient, robust information gathering and behavior in robotics. Experimental results on a shopping request identification problem show significant improvements on both efficiency and accuracy, compared with existing approaches using P-log or POMDPs individually.

One direction of future investigation is to apply CORPP to problems of larger scales by programming with P-log using SCOU grammar (more strict but not fully declarative) (Zhu 2012) and using N-best and/or factorized POMDPs (Young et al. 2013). Another possible direction is to apply CORPP to a team of intelligent robots with a shared knowledge base.

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References

Baral, C.; Gelfond, M.; and Rushton, N. 2009. Probabilistic Reasoning with Answer Sets. *Theory and Practice of Logic Programming* 9(1):57–144.

Gelfond, M., and Kahl, Y. 2014. *Knowledge Representation, Reasoning, and the Design of Intelligent Agents: The Answer-Set Programming Approach.* Cambridge University Press.

Halpern, J. Y. 2003. Reasoning about uncertainty.

Kaelbling, L.; Littman, M.; and Cassandra, A. 1998. Planning and Acting in Partially Observable Stochastic Domains. *Artificial Intelligence* 101:99–134.

Kurniawati, H.; Hsu, D.; and Lee, W. S. 2008. Sarsop: Efficient point-based pomdp planning by approximating optimally reachable belief spaces. In *Robotics: Science and Systems*.

Milch, B.; Marthi, B.; Russell, S.; Sontag, D.; Ong, D. L.; and Kolobov, A. 2005. BLOG: probabilistic models with unknown objects. In *Proceedings of the 19th international joint conference on Artificial intelligence*.

Quigley, M.; Conley, K.; Gerkey, B. P.; Faust, J.; Foote, T.; Leibs, J.; Wheeler, R.; and Ng, A. Y. 2009. ROS: An Open-Source Robot Operating System. In *Open Source Software Workshop*.

Richardson, M., and Domingos, P. 2006. Markov logic networks. *Machine Learning* 62(1-2):107–136.

Roy, N.; Pineau, J.; and Thrun, S. 2000. Spoken dialogue management using probabilistic reasoning. In *the Annual Meeting on Association for Computational Linguistics*.

Walker, W.; Lamere, P.; Kwok, P.; Raj, B.; Singh, R.; Gouvea, E.; Wolf, P.; and Woelfel, J. 2004. Sphinx-4: A flexible open source framework for speech recognition.

Young, S.; Gasic, M.; Thomson, B.; and Williams, J. D. 2013. Pomdp-based statistical spoken dialog systems: A review. *Proceedings of the IEEE* 101(5):1160–1179.

Zhang, S.; Sridharan, M.; Gelfond, M.; and Wyatt, J. 2014a. Towards an architecture for knowledge representation and reasoning in robotics. In *Social Robotics*. Springer. 400–410.

Zhang, S.; Yang, F.; Khandelwal, P.; and Stone, P. 2014b. Mobile robot planning using action language $\mathcal{BC}$ with hierarchical domain abstractions. In *The 7th Workshop on Answer Set Programming and Other Computing Paradigms (ASPOCP)*.

Zhang, S.; Sridharan, M.; and Bao, F. S. 2012. ASP+POMDP: Integrating Non-monotonic Logic Programming and Probabilistic Planning on Robots. In *International Conference on Development and Learning and on Epigenetic Robotics (ICDL-EpiRob)*.

Zhang, S.; Sridharan, M.; and Washington, C. 2013. Active visual planning for mobile robot teams using hierarchical pomdps. In *IEEE Transactions on Robotics*.

Zhu, W. 2012. *PLOG: Its Algorithms and Applications*. Ph.D. Dissertation, Texas Tech University, USA.