درس شیوه ارائه مطالب فنی

سال تحصیلی 97-98

ترم بهار

لطفا پیش از پاسخگویی به تمرین به نکات زیر توجه فرمایید:

۱ - موعد تحویل تمرین ۳۱ اردیبهشت ماه ساعت۲۳:۵۵ است.

۲- هدف از این تمرین آشنایی با بخش نتیجه گیری می باشد.

۳- نکاتی را که در کلاس درس بیان شده اند درنظر بگیرید.

۴- تمرین خود را در قالب یک فایل PDF و با فرمت HW4_8101???? آپلود کنید

بخش نتیجه‌گیری یک مقاله می‌تواند شامل موارد زیر باشد:

1. **ارجاع به هدف یا فرضیه اصلی مورد مطالعه**
2. **خلاصه مهم‌ترین یافته‌ها**
3. **بحث و توضیح راجع به علل نتایج(تبیین ارزش تحقیق)**
4. **محدودیت‌های مطالعه**
5. **نتایج ضمنی مطالعه**
6. **تحقیقات آتی**

*** در نتیجه‌گیری‌های زیر موارد مذکور را مشخص نمایید.**

*** دقت داشته باشید همه موارد بالا ممکن است در نتیجه‌گیری آورده نشده باشند.**

Conclusion 1 :

In this paper we presented a novel approach for general opponent modeling, proposing offers using a concession method and accepting offers using a sophisticated threshold. We showed that our approach allows the automated agent negotiate efficiently with people and even perform better than another state-of-the-art automated agent. The results demonstrate that the *KBAgent* achieved significantly higher utility values than the human players. In comparison to the other automated agent (the *QOAgent*) it achieved higher utility values and in the case of one of the two roles, even achieved significantly higher utility values. As people negotiate in diverse ways and mostly in one-shot negotiations a general opponent modeling approach could yield better results than specific opponent modeling, as we indeed shown in the experiments. Moreover, the approach we apply has a low computation complexity and can work well on sparse databases. Future work will match the *KBAgent* on additional domains to test the generality of its design and to bolster the confidence of the generated results.

Conclusion 2 :

In this paper, we developed a framework that can be used by an agent to learn models of other agents in a multi-agent system. The framework makes use of influence diagrams as a modeling representation tool. We addressed three strategies to create a new model of the other agent, which are based on learning its capabilities, preferences, and beliefs, given an initial model and the agent's behavior data. We presented a method for learning the agents' capabilities, and our preliminary ideas on how to learn the beliefs, but we concentrated and gave examples on learning of the other agent's preferences. Our method attempts to modify the other agent's utility function by incorporating a neural network learning technique, which involves the presentation of the history of other agent's observed behavior as the training set and a series of weight adjustments. The new model for the agent is created by replacing the initial model's utility function with the one produced by our method. To assign the probability to the new model being correct, we allow it to compete with other models we have by presenting the history of behavior and performing probabilistic update based on how well each model predicts the behavior. In our future work we will implement the learning algorithm for modifying another agent's beliefs, and we will integrate all of the learning algorithms

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Conclusion 3 :

This paper evaluates and compares the performance of a selection of state-of-the-art online opponent models. The main goal of this work is to evaluate if, and under what circumstances, opponent modeling is beneficial. Measuring the performance of an opponent model is not trivial, as the details of the negotiation setting affects the effectiveness of the model. Furthermore, while we know an opponent model improves the negotiation outcome in general, the role of time should be taken into account when considering online opponent modeling in a realtime negotiation because of the time/exploration trade-off: a computationally expensive model may produce predictions of better quality, but in a real-time setting it may lead to less bids being explored, which may harm the outcome of the negotiation. Based on an analysis of the contributing factors to the quality of an opponent model, we formulated a measurement method to quantify the performance of online opponent models and applied it to a large set of state-of-the-art opponent models. We analyzed two main types of opponent models: frequency models and Bayesian models. We noted that the time/exploration trade-off is indeed an important factor to consider in opponent model design of both types. However, we found that the best performing models did not suffer from the trade-off, and that most – but not all – online opponent models result in a significant improvement in performance compared with not using a model; not only because the deals are made faster, but also because the outcomes are on average significantly closer to the Pareto-frontier. A main conclusion of our work is that we noted that frequency models consistently outperform Bayesian models. This is not only because they are faster, because the effect remains in a round-based setting. This suggests that frequency models combine the best of both worlds. Surprisingly, despite their performance, frequency models have not received much attention in literature. Our other main conclusion concerns the effects of the negotiation setting on an opponent model's effectiveness. We found that the more competitive an agent, or its opponent, the more benefit an opponent model provides. In addition, we found that the higher the size or the bid distribution of a scenario, the higher the gain of using a model. For future work, it would be interesting to examine other uses of opponent modeling, such as opponent prediction. Another direction of future work is to investigate the interaction between opponent model performance and its accuracy through time. We also plan to test a larger set of models derived from literature and ANAC 2012.