Coach Version	Round 2 Score	Round 3 Score
Round 2	48,240	-
Round 3	45,961	78,680

Table 2: Average scores for the current and Round 2 version of the coach on patterns from Round 2 and Round 3. The scores for the Round 3 coach are averaged over 10 games each. The score of the Round 2 coach on the Round 2 data was averaged over 5 games.

that UT Austin Villa was indeed the rightful champion of the competition. Our coach appears to be at least as strong as the competition results indicate. At the same time, because we do not have as many data points for the other coaches, it is possible that the competition results underrepresent their true performance.

Related Work

Some previous work has been done on learning to give advice to RoboCup simulated soccer players. Riley et al. (2002) approached advice-giving as an action-prediction problem. Both offensive and defensive models were generated using the C4.5 (Quinlan 1993) decision tree learning algorithm. Their work also stressed the importance of learned formation advice. Subsequently, Kuhlmann et al. (2005) decomposed the problem similarly, but using different model representations and advice-generation procedures.

In other work, Riley and Veloso (2002) used Bayesian modeling to predict opponent movement during set plays. The model was used to generate adaptive plans to counter the opponent's plays. In addition, Riley and Veloso (2000) have tried to model high-level adversarial behavior by classifying opponent actions as belonging to one of a set of predefined behavioral classes. Their system could classify fixed duration *windows* of behavior using a set of sequence-invariant action features.

Opponent team modeling has also been studied in military-like scenarios. In addition to Tambe's work mentioned in the introduction (Tambe 1996), Sukthankar and Sycara (2005) use HMMs to monitor and classify *human* team behavior in a MOUT (military operations in urban terrain) scenario, especially focussing on sequential team behaviors.

Conclusion and Future Work

The RoboCup simulation coach competition presents a detailed and challenging domain for autonomous agents that is specifically geared towards opponent modeling. UT Austin Villa is a complete and fully implemented agent that advises a team of soccer-playing agents and identifies patterns in the opponent teams based on statistical patterns in their positions over time. Despite winning the 2005 RoboCup simulation coach competition, UT Austin Villa leaves much room for improvement. For example, there are many additional potential features that could boost performance within the same framework, and the announcement strategy could be extended to explicitly model the likelihood of correctness relative to the cost in score from waiting longer to announce. Ultimately, it is important to build on this work towards a team that is able to exploit the opponent model on-line as well, both in the coach competition and in other team adversarial domains.

Acknowledgements

This research is supported in part by NSF CAREER award IIS-0237699.

References

Chen, M.; Foroughi, E.; Heintz, F.; Kapetanakis, S.; Kostiadis, K.; Kummeneje, J.; Noda, I.; Obst, O.; Riley, P.; Steffens, T.; Wang, Y.; and Yin, X. 2003. Users manual: RoboCup soccer server manual for soccer server version 7.07 and later. Available at `http://sourceforge.net/projects/sserver/`.

Kitano, H.; Kuniyoshi, Y.; Noda, I.; Asada, M.; Matsubara, H.; and Osawa, E. 1997. RoboCup: A challenge problem for AI. *AI Magazine* 18(1):73–85.

Kok, J. R.; de Boer, R.; Vlassis, N.; and Groen, F. 2003. Towards an optimal scoring policy for simulated soccer agents. In Kaminka, G. A.; Lima, P. U.; and Rojas, R., eds., *RoboCup-2002: Robot Soccer World Cup VI*. Berlin: Springer Verlag. 292–299.

Kuhlmann, G.; Stone, P.; and Lallinger, J. 2005. The UT Austin Villa 2003 champion simulator coach: A machine learning approach. In Nardi, D.; Riedmiller, M.; and Sammut, C., eds., *RoboCup-2004: Robot Soccer World Cup VIII*. Berlin: Springer Verlag. 636–644.

Noda, I.; Matsubara, H.; Hiraki, K.; and Frank, I. 1998. Soccer server: A tool for research on multiagent systems. *Applied Artificial Intelligence* 12:233–250.

Quinlan, J. R. 1993. *C4.5: Programs for Machine Learning*. San Mateo, CA: Morgan Kaufmann.

Riley, P., and Veloso, M. 2000. On behavior classification in adversarial environments. In *Proceedings of the Seventeenth National Conference on Artificial Intelligence (AAAI-2000)*.

Riley, P., and Veloso, M. 2002. Recognizing probabilistic opponent movement models. In Birk, A.; Coradeschi, S.; and Tadokoro, S., eds., *RoboCup-2001: The Fifth RoboCup Competitions and Conferences*. Berlin: Springer Verlag.

Riley, P.; Veloso, M.; and Kaminka, G. 2002. An empirical study of coaching. In Asama, H.; Arai, T.; Fukuda, T.; and Hasegawa, T., eds., *Distributed Autonomous Robotic Systems 5*. Springer-Verlag. 215–224.

Stone, P. 2000. *Layered Learning in Multiagent Systems: A Winning Approach to Robotic Soccer*. MIT Press.

Sukthankar, G., and Sycara, K. 2005. Automatic recognition of human team behaviors. In *Proceedings of Modeling Others from Observations, Workshop at the International Joint Conference on Artificial Intelligence (IJCAI)*.

Tambe, M. 1996. Tracking dynamic team activity. In *National Conference on Artificial Intelligence(AAAI96)*.

Veloso, M.; Stone, P.; and Bowling, M. 1999. Anticipation as a key for collaboration in a team of agents: A case study in robotic soccer. In Schenker, P. S., and McKee, G. T., eds., *Proceedings of SPIE Sensor Fusion and Decentralized Control in Robotic Systems II*, volume 3839, 134–143. Bellingham, WA: SPIE.