Graphical Multiagent Models
(Extended Abstract)

Quang Duong
qduong@umich.edu
Computer Science and Engineering
University of Michigan, Ann Arbor, MI 48104, USA

ABSTRACT

I introduce a graphical representation for modeling multiagent systems based on different kinds of reasoning about agent behavior. I seek to investigate this graphical model's predictive and representative capabilities across various domains, and examine methods for learning the graphical structure from agent interaction data. I also propose to explore the framework's scalability in large real-world scenarios, such as social networks, and evaluate its prediction performance with existing network behavior models.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Distributed Artificial Intelligence

General Terms

Design, Experimentation

Keywords

Graphical Models, Game Theory, Behavioral Modeling

1. INTRODUCTION

Large complex multiagent systems, such as financial markets, social groups, and computer networks, present great challenges to multiagent system researchers seeking to compactly represent these systems' dynamics and effectively predict their outcomes. Although modeling agents as perfectly rational decision makers is a common starting point in many efforts, we still need to account for agents' bounded rationality in real-world scenarios. There is also the question of which equilibrium agents will converge on, if there are more than one such equilibrium. The computational complexity of inferences in large systems further renders behavior modeling for such systems intractable.

These observations motivate my probabilistic approach to modeling multiagent systems of decomposable structure. As multiagent scenarios often exhibit localized effects of agent interactions, graphical models have played an important role in exploiting these conditional independencies, as illustrated in the graphical game models [6]. In the graphical game approach, the model is a factored representation of a normal-form game, on which special-purpose techniques, such as the mapping of a graphical game onto a Markov random field (MRF) [1], operate to identify approximate or exact Nash equilibria. I combine game-theoretic principles and graphical models in a novel representation framework: *graphical multiagent models* (GMMs) [4]. The GMM representation takes advantage of the locality in agent interactions to enable efficient reasoning about collective behavior based on game-theoretic solution concepts, which are formal rules for predicting how the game will be played, and other kinds of reasoning about agent behavior using knowledge unrelated to game-theoretic analysis.

In my thesis work, I seek to investigate GMMs' predictive and representative capabilities across various domains, with a focus on scenarios where information on different system elements such as agent connections, their utility, or past actions, is limited or unavailable. I first examine the extent of prediction improvement GMMs can gain from combining different beliefs about agent behavior. I further extend the GMM framework to account for historical information in time-variant scenarios, and empirically demonstrate its robustness to the limitedness of information regarding past actions and agent connections, respectively in two domains of voting consensus and information diffusion. As graphical structures capturing agent interactions are often only partially observed or entirely missing, I also examine different methods for learning agent connections from data about agent interactions. To expand GMMs' applicability, I will explore their scalability in large real-world scenarios, such as social networks, by introducing new GMMs for these scenarios, and evaluating their prediction performance with existing network behavior models.

2. GRAPHICAL MULTIAGENT MODELS

GMMs simply graphical models where each neighborhood of nodes is associated with a potential function specifying the likelihood that a particular action profile of the neighborhood is included in the global action profile [4]. The normalized product of these potentials induces the joint distribution of actions, which can be interpreted as an uncertain belief (e.g., a prediction) about the agents' play. Unlike the aforementioned mapping from graphical games to MRFs, the GMM framework allows beliefs to be based on various solution concepts, models of bounded rationality or equilibrium selection, or for that matter knowledge that has nothing to do with game-theoretic analysis. GMMs provide a

Cite as: Graphical Multiagent Models (Extended Abstract), Quang Duong, *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2011)*, Tumer, Yolum, Sonenberg and Stone (eds.), May, 2–6, 2011, Taipei, Taiwan, pp. 1351-1352.

flexible representation framework for graphically structured multiagent scenarios, supporting the specification of probability distributions based on game-theoretic models as well as heuristic or other qualitatively different characterizations of agent behavior. They are capable of incorporating different knowledge sources in different forms such that the resulting models have better predictive power than either input source alone [4].

2.1 History-dependent GMMs

To capture dynamic behaviors over time, I extended the static GMM framework to condition on history, creating *history-dependent graphical multiagent model* (hGMM) [3]. Finite memory and computational power often preclude complete retention of historic observations in inferring about future actions. From the perspective of the system modeler, only a partial view of the full history may be available. Given a summarized or abstracted history representation, agent decisions will generally appear correlated, even if they are independently generated conditional on full history.

Unlike *individual behavior models* that assume independence among agents' decisions, GMMs and hGMMs directly specify joint behaviors. Thus, hGMMs can account for correlations in agent actions without full specifications of the state history mediating agent interactions, and can answer queries regarding the distribution of agents' future actions without sampling the entire system's history. I empirically showed [3] that hGMMs outperform individual behavior models in predicting data and answering inference queries in the domain of voting consensus experiments [5].

2.2 Model Construction

The underlying graphical structures are often not readily constructed for many real-world scenarios. In my thesis, I provide system modelers with techniques for building GMM representations of different scenarios, given knowledge from different sources about the systems at hand. In particular, I address the problem of learning graphical games given payoff observations, and evaluated an array of structural learning algorithms for graphical games [2]. I also extend that study to propose and examine a greedy algorithm for learning both the model's parameters and graphical structure of some predetermined complexity, given action observations in non-game scenarios.

3. FUTURE WORK

3.1 Extensions on Model Construction

Instead of imposing a predetermined hard constraint on the maximum degree of each node, which is non-trivial to estimate for unknown scenarios, I will incorporate cross-validation into determining termination conditions of the revamped learning algorithm. As a result, there will be no need to impose a complexity constraint given little knowledge about the multiagent system at hand. In a different effort to address the problem of graphs' complexity and improve GMMs' scalability, I plan to adopt community identification algorithms based on nodes' properties [9] in constructing factored representations that specify joint behaviors within groups while assuming behavioral independence among these groups.

3.2 Network Applications

Researchers have taken advantage of the availability of massive amounts of data in analyzing and understanding how information diffuses in different communities and social networks, such as product marketing or movie recommendations among online social network friends [8]. In actuality, not all connections among different parties are visible to the modelers. For instance, studies on online social network often overlook a myriad of offline interactions. I will address the problem of modeling information infusion on networks with unobserved connections in two different approaches: constructing hGMMs that can compensate for this lack of information by explicitly specifying joint behaviors, and learning the underlying graphical structure using observation data. I will demonstrate each approach's strengths and weaknesses in different input settings.

While the application of GMMs in social network analyses can potentially enrich the field, the GMM framework can also benefit from exploring this problem domain. In addition to studying how information diffuse in networks, I will investigate how network connections are formed. By treating the act of establishing a connection as an action, a GMM representation can capture the network's formation and evolution, having the benefits of a joint behavior model, as in the aforementioned problem of modeling information diffusion. I will develop joint behavior hGMMs that employ strategic elements in agents' interactions based on existing network formation models [7]. This application of GMMs can potentially broaden the GMM framework's applicability for reasoning and understanding not only behavioral phenomena on a network but the network's evolution itself.

4. REFERENCES

[1] C. Daskalakis and C. H. Papadimitriou. Computing pure Nash equilibria in graphical games via Markov random fields. In *Seventh ACM Conference on Electronic Commerce*, pages 91–99, Ann Arbor, Michigan, 2006.

[2] Q. Duong, Y. Vorobeychik, S. Singh, and M. P. Wellman. Learning graphical game models. In *Twenty-First International Joint Conference on Artificial Intelligence*, pages 116–121, Pasadena, California, 2009.

[3] Q. Duong, M. Wellman, S. Singh, and Y. Vorobeychik. History-dependent graphical multiagent models. In *Ninth International Conference on Autonomous Agents and Multiagent Systems*, pages 1215–1222, Toronto, Canada, 2010.

[4] Q. Duong, M. P. Wellman, and S. Singh. Knowledge combination in graphical multiagent models. In *Twenty-Fourth Conference on Uncertainty in Artificial Intelligence*, pages 153–160, Helsinki, Finland, 2008.

[5] M. Kearns, S. Judd, J. Tan, and J. Wortman. Behavioral experiments on biased voting in networks. *Proceedings of the National Academy of Sciences*, 106(5):1347–1352, 2009.

[6] M. Kearns, M. L. Littman, and S. Singh. Graphical models for game theory. In *Seventeenth Conference on Uncertainty in Artificial Intelligence*, pages 253–260, Seattle, 2001.

[7] R. Kumar, J. Novak, and A. Tomkins. Structure and evolution of online social networks. In *Twelveth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 611–617, Philadelphia, PA, USA, 2006.

[8] J. Leskovec, L. Adamic, and B. Huberman. The dynamics of viral marketing. *ACM Transactions on the Web*, 1(1):5–43, 2007.

[9] J. Leskovec, K. J. Lang, A. Dasgupta, and M. W. Mahoney. Community structure in large networks: Natural cluster sizes and the absence of large well-defined clusters. *CoRR, abs/0810.1355*, 2008. unpublished.