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(Extended Abstract)

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1. GAME DESCRIPTION AND NOTATION

We consider games with the following characteristics. The scene is visible to all players. Each player has a set of actions, which have an effect on the state of the scene. The players act concurrently, and the joint effect of the two actions may be non-deterministic. Each player is assigned a score, which is a function of the state of the scene, and it does not change during the game. This assignment is known only to the player. We assume everything to be finite, and we consider games with only two players. We shall call this kind of games a Simple Sequential Bayesian Game (SSBG).

Formally, an SSBG consists of two players ♦, ♠ and a world W with a finite set of states. We assume ♦ to be female and ♠ to be male. The players have finite sets of moves, M♦ and M♠, which affect W. The transition between world states at time t to time t + 1 is determined by a probabilistic function τ, τ : W × M♦ × M♠ × W → R, where τ(w1, m♦, m♠, w2) is the probability of Wt+1 being in state w2 given that Wt was in state w1 and the two players make the moves m♦ and m♠, respectively. Furthermore, each player draws an assignment from a finite set A. The assignment is a particular score function reflected in utility numbers over states of the world. We shall assume that ♦ has received the assignment a1. The structure of the game and the world state is always known by both players, but the actual assignment of the other player remains hidden.

When both players have decided their moves, the game continues with the next time step. There is no prefixed limit on the number of moves, but the time for playing the game is so short that discounting is not relevant. That is, the players aim for maximizing the sum of the utilities gained during the game.

2. RECURSIVE INFLUENCE DIAGRAMS

An RID ([6]) is a dynamic influence diagram [7] that models the agent’s subjective decision-theoretic reasoning and its reasoning about other agent’s reasoning. Figure 1 shows an RID modeling an SSBG as seen in the eyes of ♦. The model consists of 3 influence diagrams, namely the A-Model, B-Model and the λ-Model, representing ♦’s model, ♦’s model of ♠ and ♦’s model of ♠’s model of ♦ respectively.

RIDs follow the same notations and conventions as influence diagrams [2]. The nodes labeled A♠ and A♦ represent the assignments; the nodes labeled with M represent moves; the U-labeled nodes represent score functions, and the Ws represent the world states. The transition function is represented by the conditional probability P(Wt|Wt−1, M♦, M♠).

The connection between the A-Model, the B-Model and the λ-Model is as follows: in the A-Model, ♦’s own decisions are represented as decision nodes while she represents ♠ decisions as chance nodes. That means that the policy for ♠ in each of his decisions must be represented as a conditional probability distribution. To find these, ♦ consults the B-Model - which in this case is another RID but this time representing the game in the eyes of ♠. In the B-Model, ♠’s decisions are represented as decision nodes and ♦’s decisions as chance nodes. The models can be solved using standard algorithms for solving IDs (see for instance [3, 4, 5]).

Probabilistic Graphical Models (PGMs) have previously been applied in opponent modeling frameworks [1, 8]. As opposed to those, RIDs have proven particularly effective in solving SSBGs [6].


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When the tree is solved, the appropriate conditional probability table for optimal policies in the leaves. They are used to determine the probability assigned to each subtree.

2.1 The Player Representation

RIDs have inherent assumptions about how many future time steps \( \heartsuit \) is considering, how many future time steps \( \spadesuit \) thinks \( \clubsuit \) is considering. Furthermore, RIDs have inherent assumptions about how deep \( \spadesuit \)'s nesting level is. In Figure 1 the A-Model, the B-Model and the A-Model takes 2, 2 and 1 future time steps into account respectively, and the nesting level of the A-Model is 3.

3. TYPE TREES

To model the uncertainty of the opponent’s assignment we use type trees. A type tree is a data structure that can be used to represent \( \spadesuit \)'s probability distribution over \( \clubsuit \)'s assignment. It can also represent \( \spadesuit \)'s beliefs of \( \clubsuit \)'s belief of \( \heartsuit \)'s assignment etc (see Figure 2).

Each internal node in a type tree represents an action agent, and we have to find the policy for each of them. So, we attach an influence diagram to each internal node.

3.1 Solving the type tree with IDs

The tree is solved from the leaves and up to the root. Taking the type tree in Figure 2, we first calculate the nine optimal policies in the leaves. They are used to determine the conditional probability table for \( M^\spadesuit \) in the parents.

Next, the 3 IDs under the root are solved to provide the appropriate \( \clubsuit \)-policies, which finally are used for solving the ID in the root. When the tree is solved, \( \spadesuit \) uses the recommendation from the model to decide for a move. \( \clubsuit \) also makes a move and both observe a new state of \( W \). \( \spadesuit \) uses the new information to update the parameters of the model, and the updated model is used to determine the next move. That is, when deciding the next move, she uses the same time horizon and nesting depth as the first move.

3.2 Updating the type tree

When both players have taken a move and the resulting world state is observed, they shall use the new information to update their beliefs in order to determine their next move. This means that \( \spadesuit \) has to update her type tree. If the moves are public, standard Bayesian network (BN) algorithms are used for the updating. In the case of private moves, the private information grows during play, and the type tree grows exponentially. We address this problem in a separate paper.

4. MIXTURE MODELS FOR ADAPTATION

Formally, let \( \Gamma_1, \ldots, \Gamma_k \) be models. Then a mixture model can be denoted as

\[
\Gamma = \sum_{i} \mu_i \cdot \Gamma_i,
\]

where \( \mu_i \) are positive reals for which \( \sum \mu_i = 1 \). We treat them as probabilities reflecting \( \spadesuit \)'s belief in the various models. When calculating the policies in \( \Gamma \), you combine the appropriate policies from the \( \Gamma_i \)-models as the sum weighted by the beliefs. Now, when information \( e \) has been collected, the probabilities for the various models change. Let \( P(e|\Gamma_i) \) denote the probability of the evidence \( e \) if \( \clubsuit \) plays in accordance with \( \Gamma_i \). Bayesian conversion yields \( P(\Gamma_i|e) \approx P(e|\Gamma_i)P(\Gamma_i) \), and standard BN algorithms provide \( P(e|\Gamma_i) \) for all \( i \), and we can use the collected information about \( \clubsuit \)'s moves to adapt the mixture to his actual reasoning.

Over time inconsistency may emerge in the models. At time step \( t \), \( \spadesuit \) receives observations and needs to update her type tree \( T_t \). If the observations are inconsistent with \( T_t \) (i.e. the joint observations have probability 0 according to her model), Bayesian updating becomes invalid and \( \spadesuit \) will have no way of assessing the probabilities of \( T_{t+1} \). This is a general problem in opponent modeling techniques. When \( \spadesuit \) has a model of \( \clubsuit \), it will inevitably contain a wrong model of \( \spadesuit \) (otherwise the model would be infinite) and inconsistent observations will eventually emerge. We have resolved the conflict by adding a baseline model, \( \Gamma_0 = \text{NIL} \), that prescribes random behavior. As \( \Gamma_0 \) hypothesizes all possible actions, updating is always possible.

5. REFERENCES