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Computational ability in games: Individual difference and dynamics

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ABSTRACT

In games especially large scale extensive games, players' actual views of the game might be different from the real one, because of the limit of their computational power. Moreover, players' views on the underlying game vary from person to person. Based on some existing work on modelling players' limited foresight in games, we study several interesting types of players in terms of the characteristics of their actual views. The underlying model is closely connected to the well-known algorithm called $\alpha - \beta$ pruning, and an algorithmic procedure refining classical backward-induction is designed for strategy choosing in the actual process of playing such games. Further, we study the dynamic evolution of players' foresight and show the resulting preference change.

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1. Introduction

Focusing on decision-making of players in cooperative or competitive situations to achieve optimal goals, game theory provides a series of mathematical models for explaining and predicting equilibrium and dynamics [1–4] in interactive systems [5,6], which have applications in diverse fields including social science[7], computer science [8], economics [9], biology [10–12], etc. In traditional game theory, there are two important aspects about extensive games, known as *quantified preferences over outcomes* and *assumption of common knowledge*, calling for potential improvement. A game of quantified preferences assumes that all outcomes are linearly ordered, usually determined by a utility function. However, as claimed by Slade [13], not all outcomes can be evaluated purely by utility functions in certain games. In reality, to obtain the exact payoff of an outcome is often difficult or computationally expensive, and a player is often forced to make a decision in presence of imprecise or incomplete information, in which situation two available options to a player might be incomparable to each other. Therefore, it is useful to study the notion of preference by qualitative binary relations, especially when there does not exist a linear order on all options in hand.

Another assumption in most of the existing works is that the entire structure of a game is common knowledge to all players. Again, this assumption is sometimes too strong. In a game like chess, the actual game space is exponential in the size of the game configuration, and may have a computation path too long to be effectively handled by most existing computers. Sub-optimal solutions are often desirable by considering only limited information or bounded steps foreseeable by a player that has relatively small amount of computation resources.

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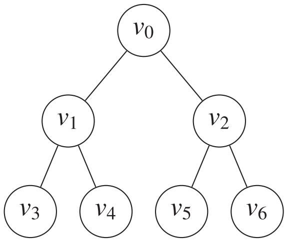

Fig. 1. An example of extensive games.

Several attempts have been made to achieve a closer match with reality. In recent years, Halpern et al. studied games with unawareness [14,15], where players may have no access to the whole game tree when they make decisions due to their unawareness of other player's strategies. Grossi and Turrini pushed further beyond Halpern's work by proposing the concept of *games with short sight* [16], in which players can only see part of the game tree. Nevertheless, Grossi and Turrini only offered a general frame for sight functions. They did not study the relationship between different classes of sight functions and players, nor did they explore dynamics of sight functions and the evolution of preference in games [17].

In this paper, we propose a more realistic model for extensive games, which represents players' preference qualitatively instead of using numeric payoffs. We outreach the initial model of extensive games with short sight in several aspects, including characterizing types of players in terms of their *sight functions*. Interestingly, we connect the $\alpha - \beta$ pruning, a well-known and realistic search algorithm for two-player zero-sum games [18], with *sight filtration*. Furthermore, in order to compute an equilibrium path of qualitative game playing, we introduce a modified backward induction algorithm. Besides, we investigate sight dynamics with respect to different types of players, and show that changes of players' sight would lead to the changes of their preferences.

This paper is organized as follows: The next section introduces extensive games and subgame perfect equilibrium. Then we study the model of games with short sight. After that, we discuss sight dynamics and preference change. Finally, we concludes the paper with further research issues.

2. Extensive games with perfect information

In this section, we recall the definition of extensive games with perfect information and subgame perfect equilibrium in these games.

Definition 2.1 (Extensive game)**.** An extensive game is a tuple $G = (N, V, A, t, \Sigma_i, \succeq_i)$, where (V, A) is a tree with V a set of nodes or vertices including a root v_0, and $A \subseteq V^2$ a set of arcs. N is a non-empty set of the players, and $\succeq_i$ is a transitive and reflexive binary relation on V for each player i, which denotes player i's preference over any two nodes. For any v and v' in V, if $(v, v') \in A$, we call v' a *successor* of v, thus A is also regarded as the successor relation. Leaves are the nodes that have no successors, denoted by Z. t is turn function assigning a member of N to each non-terminal node. Σ_i is a non-empty set of strategies. A strategy of player i is a function $\sigma_i : \{v \in V \backslash Z | \; t(v) = i\} \to V$ which assigns a successor of v to each non-terminal node when it is i's turn to move.

For a node v we write $l(v)$ for the distance from the root v_0 to v. And the depth of a game tree is the maximal distance among all the nodes, denoted as $L = \max\{l(v) | v \in V\}$. As usual, $\sigma = (\sigma_i)_{i \in N}$ represents a strategy profile which is a combination of strategies from all players and Σ represents the set of all strategy profiles. For any $M \subseteq N$, σ_{-M} denotes the collection of strategies in σ excluding those for players in M. We define an outcome function O: $\Sigma \to Z$ assigning leaf nodes to strategy profiles, i.e., $O(\sigma)$ is the outcome if the strategy profile σ is followed by all players starting from the root v_0. $O(\sigma_{-M})$ is the set of outcomes players in M can enforce provided that the other players strictly follow the strategy profile σ.

Note that the preference relation defined here is different from the conventional ones. Preference can be defined as connected, e.g.,[19], while more generally we allow the incomparable cases between two nodes, and work with a partial order over nodes in the game. We assume that players may not be able to precisely determine the entire computation paths leading to leaves, and allow them to make estimations on the goodness of non-terminal nodes. For any two nodes u and v in V, if $u \succeq_i v$ but not $v \succeq_i u$, then u is strictly preferable to v for player i, and we write it as $u \succ_i v$.

Example 2.1. Take the game shown in Fig. 1 as an example, where two players a and b take turns to move. Specifically, player a moves at v_0, and player b moves after a going to v_1 or v_2. The formal representation for the game is as follows: $G = (N, V, A, t, \Sigma_i, \succeq_i)$, where $N = \{a, b\}$; $V = \{v_0, v_1, v_2, v_3, v_4, v_6\}$; $A = \{(v_0, v_1), (v_0, v_2), (v_1, v_3), (v_1, v_4), (v_2, v_5), (v_2, v_6)\}$; $t(v_0) = a$, $t(v_1) = t(v_2) = b$; Player a has two strategies σ_a and σ'_a such that $\sigma_a(v_0) = v_1$ and $\sigma'_a(v_0) = v_2$, while player 2 has four strategies σ_b^1, σ_b^2, σ_b^3 and σ_b^4 such that $\sigma_b^1(v_1) = v_3$ and $\sigma_b^1(v_2) = v_5$, $\sigma_b^2(v_1) = v_3$ and $\sigma_b^2(v_2) = v_6$, $\sigma_b^3(v_1) = v_4$ and $\sigma_b^3(v_2) = v_5$, $\sigma_b^3(v_1) = v_4$ and $\sigma_b^2(v_2) = v_6$. Naturally, combining strategies for the two players results in 8 strategy profiles. Preference relation for each player depends on the payoffs of nodes. Suppose, e.g., player b gets a higher payoff at v_3 than v_4, then we have $v_3 \succ_b v_4$.

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