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Abstract

The Artificial Intelligence research field since ages has incorporated a series of novel and trend setting distinct approaches including neural networks, fuzzy logic and genetic algorithms to apply them to various problem-solving domains. Machine learning techniques such as evolutionary learning, neural networks and reinforcement learning alone are difficult to apply to board games because they need an extremely large number of computations which are having tendency to increase exponentially in numbers as the search depth increases to find better move(s). Many board game researchers find that machine learning approach through evolutionary learning using some optimization methods like genetic algorithm gives better

results to build robust and better artificially intelligent game playing programs. In case of board game, board squares plays vital role in terms of exploring the game based topographies to assign relative weight to board squares as per their positions. These weight assignments in game-playing programs are derived through quality search and rules acquaintance and game playing experience. When the move search reaches the end of a game tree structure, attained optimized evaluation function values are used to assess board position “goodness”. The paper takes Game of Reversi as its object game and exploits its symmetric phenomenon to develop genetically evolutionary game playing program to learn its impact on the evolution of weight values for a particular disc sets through weight value land scape. The collected results for the said disc sets endorse the earnest efficacy of genetic algorithm as an evolutionary optimization instrument. The first two sections is about game introduction and game search space. The next section discusses history of game program development and game playing phases. Section five and six aims game of Reversi implementation and collected results respectively. The last two sections are about conclusion and references.

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Game of Reversi
Board Square Weight