Solving Heads Up Texas Hold’em Style Poker Games

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CS 490 Abstract

No limit Hold’em is the most common variant of the family of card games popularly known as poker. Due to the history and popularity of no limit Hold’em, there have been many attempts to solve the game. Most recently, the Libratus Poker AI beat four professional players in heads up (one versus one) poker at a rate of 14.7 big blinds per 100 hands, which is a rate most professionals would not be able to make themselves against weaker players. In this project, we attempt to create a bot that can play games similar to Hold’em using similar reinforcement learning techniques.

We use a technique called counterfactual regret minimization, a form of reinforcement learning. Regret minimization begins with a random strategy, and on each iteration it calculates the regret of each action it makes based on the each action’s utility. Then, the new probability distribution of actions at each step is calculated using these regret values. This process is iterated as many times as necessary until the average strategy converges towards a Nash Equilibrium. This process guarantees such a convergence, but for games with as many possibilities as no limit Texas Hold’em, the algorithm requires too many iterations to converge in a reasonable amount of time. Techniques such as partial pruning can reduce the time required to compute the optimal strategy drastically.

In this paper, we implement the regret matching algorithm for counterfactual regret minimization. We make several simplifying assumptions to reduce the complexity of the game and implement pruning techniques such as partial pruning to solve the game in a much shorter
amount of time. The final algorithm can be used to solve a wide variety of games similar to Texas Hold’em, and we present a few examples of the calculated optimal strategies.