**Project Proposal: Machine Learning Engine for Ninety-Nine**

Artificial Intelligence (AI) has captured the imagination of the public for well over a century, and the field has become a source of research and innovation over the past decade. AI has been harnessed for great practical use in many domains, including image processing, natural language generation, scientific analysis, and more. Many of these practical uses are built on techniques which were first applied to game-playing systems. There is a long history of AI developers using game-playing to study decision-making between competitive agents (Amit et al., 2006). The first game engines attempted by AI researchers played games of perfect information, such as Chess and Checkers. Games of partial information, such as card games, add another layer of complexity. This capstone project seeks to develop a game-playing engine for the card game Ninety-Nine, contributing to the speed and accuracy of decision-making systems under limited information environments.

**Section 1: Background**

Artificial Intelligence game-playing engines have tended to fall into two broad categories, statistical analysis and self-play. Of the first category, Monte Carlo Simulation is a promising technique for games of partial information such as Ninety-Nine. Of the second category, Reinforcement Learning has seen much success at many different types of problems.

* 1. **Monte Carlo Simulation:**

Many card-playing systems utilize Monte Carlo Simulation during card play (Ginsberg, 1999). This ingenious technique involves two steps: First, a solving algorithm is able to quickly analyze the best play for a *perfect information* scenario, a version of the game where all players’ hands are known. To determine the best move for the *partial information* scenario, the computer randomly samples possible game states based on known information such as the cards in its own hand and the cards played so far, using the perfect information solver to determine what the best card to play would be for this distribution. It then uses these possible game states to vote on the best card to play in the partial information scenario, and plays that card.

* 1. **Reinforcement Learning:**

Another approach game engines take (especially more recent engines) is called Reinforcement Learning. This approach involves neural networks which are trained by attempting the process over and over. The AI will update its parameters on an unsuccessful attempt through gradient descent and backpropogation, resulting in the fine-tuning of the connection between its inputs (the environment of the program, such as the current state of the player’s hand and the cards played so far) and its chosen output (the action to take, such as playing a card). One specific version of this approach is the Actor-Critic method (Wang et al., 2017).

**Section 2: Previous Works**

Game-playing is a unique field for Artificial Intelligence (AI) research, providing a variety of opportunities in a discrete, simplified environment. While many engines have been developed to play perfect-information games over the past several decades, high-level AIs in the domain of partial-information games have been a more recent phenomenon. This section reviews previous milestones in the history of game-playing AI.

Perfect-information games: Chess was one of the first games to be studied by programmers, culminating in the engine Deep Blue that was able to beat a grandmaster, Garry Kasparov, in a full chess match. Several decades later, a neural network-based system called AlphaZero defeated the top conventional chess engines at the time, and another AI by the same company also defeated the human champion at the game Go, which previous engines had been unsuccessful at.

Partial-information games: One of the first card-playing programs to rival human opponents was GIB, created to play the game Bridge (Ginsberg, 1999). This program used a Monte Carlo approach to decide which cards to play. Another team developed a similar AI to play the European game Skat (Kupferschmid et al., 2006). A more recent program developed by NukkAI incorporated reinforcement learning techniques to achieve super-human play as the declarer in Bridge (Cazenave et al., 2020).

**Section 3: Problem Statement**

The specific problem that this capstone project seeks to address is how to achieve human-level play from an Artificial Intelligence at the game of Ninety-Nine. Ninety-Nine is a trick taking game created by the card game historian and inventor David Parlett and recognized as a complex and interesting game by the card-playing world (Parlett).

As a trick-taking game, it is similar to the games of Bridge, Hearts, and Skat which have been played by game engines in the past. However, it is sufficiently different in that it is an exact trick game, where extra points are earned for correctly predicting the number of tricks that will be taken. Another innovation in the gameplay is that the bid is made by discarding three cards from each player’s hand, which is another difficult decision the computer player will have to make.

This capstone project will involve the development of different variations of engines in competition against each other and human players, with experimentation to determine which approach results in the best engine, the engine that can win the majority of games against a variety of opponents. The results may be interesting for future developers of game-playing AI.

**References:**

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