In any non-cooperative game with multiple agents, a Nash Equilibrium is a set of strategies such that, if each agent were to know the strategies of the other agents, they would not opt to change their own.

In zero-sum, two-player, alternating games, the minimax strategies form a Nash Equilibrium. This strategy set which can be found by backwards induction, minimizes the maximum expected loss for each player. This strategy is appealing for an agent, since it is the best possible strategy against a perfectly intelligent opponent who knows said agent's strategy. In this sense, it minimizes the risk that an agent is taking on.

Playing a Nash Equilibrium, as minimax is, in a zero sum game further has the advantage that any deviations from the opponent's corresponding strategy in the Nash Equilibrium can only result in additional gain for the agent playing the other Nash Equilibrium. Thus, the strategy performs optimally against the corresponding Nash Equilibrium strategy, and the payouts only increase as the opponent deviates.

Empirically, especially in complicated games, the minimax strategy may be suboptimal. The assumptions that your opponents are rational and will
jump to exploit deviations you make from the minimax strategy are sometimes not true. In these situations, while minimax still minimizes an agent's maximum potential loss, it fails to exploit opponents' weaknesses as well as it could. For example, the minimax strategy for a repeated game of Rock-Paper-Scissors is to randomize your throw each time with equal weight. However, against an opponent who, for some reason, only chooses to throw rock, this strategy clearly is suboptimal.

An opponent who only throws rock is unfathomable. In poker, however, an opponent who chooses to over-bluff, play too large a range of hands, be too passive, or reliably make any number of mistakes, is common. Taking a strategy that works well against strong opponents and playing it against weak opponents such as these will likely yield a profit, but certainly not maximize the profit you can make.

Assuming that you are sufficiently bankrolled, to go into a casino and play the same strategy at the 1-2 limit table as the 100-200 limit table is to not maximize your profits, even if you can turn a profit at each table doing this. To date existing research on computing and poker focus on building "good" poker programs in the traditional sense, that is, programs that perform well against other good programs. There is shockingly little or no research in the area of building programs to recognize and exploit weaknesses in bad programs. In real life poker, bad players are common,
and understanding how to best exploit bad play is an inquiry that is important to game theory, computing and poker.

Determining the optimal way to exploit bad play is a complicated task. Deviating from Nash Equilibrium strategy exposes a player to risk of being exploited themselves. As only hands taken to the end are typically seen, information can come at a cost. Since only a certain number of hands will be played, the proper balance between gathering information and moving to exploit it must be struck. My study hopes to shed insight on these sorts of questions as to better understand the optimal way to move to exploit poor players.

By building a parameterized space of bots in Limit Hold'Em, I hope to investigate different methods of exploiting weaknesses in the best manner possible. My initial approach will likely focus on Three-Card Poker as a simplified model with a known Nash Equilibrium, and then investigating how to best adapt strategies against bots whose parameters deviate from this.

One particularly approach I intend to investigate is a bot that stores as "capital" errors made by opponents, and only attempts to exploit these weaknesses when it has amassed sufficient capital so that if the opponent
were to anticipate its exploitation, it would still do as well as minimax, since any later attempts of counter-exploitation by an opponent would be earned at the “cost” of initial poor play.

With luck, the Three-Card poker approach will reveal strategies that can then be tested and applied to a parameterized simplified AI in Limit Hold’Em, first heads up, and potentially even multiway. Hopefully, the findings will reveal insight into adapting against suboptimal opponents in not just poker, but games of incomplete information in general.