CPSC 540 Project Proposal: Modelling Human Behaviour in Board Games

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Board games provide environments with precise rules and well-defined state spaces where the optimal decisions are still not obvious. This structure makes board games particularly attractive for AI researchers, who have developed programs for playing a variety of board games over the past decades. These programs are often designed with a goal of maximizing performance, and they have succeeded in many games: the best AI in checkers, chess, Go, and poker are hailed as being superhuman, beating the top professionals in each of these games. However, these programs tend to have the ability to "grind out" wins from slight advantages, giving them a distinctively cold, calculating style that is quite different from human play,

In this project, our goal is to develop a predictive model that can **play a board game like a human**, with a particular focus on modelling amateur play. In other words, instead of treating board games as optimization problems, we plan to treat them as supervised learning problems, using past data about people's actions to predict their moves in the future. We note that emulating human play is often a first step in building AI for many games, but these efforts are usually focused on predicting professional players' moves, and they are typically meant to bootstrap a more complex deep learning process.

The motivation for this project is threefold:

- First, modelling human behaviour is fundamentally valuable to behavioural economics. Behavioural game theory models are typically evaluated using data about human decisions in lab experiments. These datasets are limited in size, and they only capture human decisions in a laboratory environment. Accurate predictive models of human play in board games could allow us to evaluate these economic models on much larger, in-the-wild datasets.
- Second, modelling other agents is a key component of many AI problems. In 2019, the cooperative card game Hanabi was described as a "new frontier in AI research"[1]. What makes Hanabi difficult is an *equilibrium selection* problem: there are many good strategies, and it is impossible to use self-play alone to determine which strategy the rest of the team will use. Modelling the actions of other players is crucial for developing AI – specifically for Hanabi, and more generally for cooperative problems.
- Third, most weak board game AI is unsatisfying to play against! In chess, weak bots are often made from strong bots by giving them a small probability of playing a random move. This design produces bizarre behaviour: in some matches, they play almost perfectly, while in others, they make obvious blunders. Human-like AI would have enormous value to many board game communities.

Specifically, we are interested in predicting human moves in one of two games: chess or Hanabi. In either case, we can easily evaluate the performance of our model using a hold-out set or through cross-validation. These two games are attractive because they have large datasets of amateur play and communities that are supportive of AI development, but few efforts to model human play:

- **Chess:** Lichess[2] is a popular chess server that posts an archive of all of their games each month. In recent months, these archives contain roughly 40 million games, amounting to a

[1] `https://arxiv.org/abs/1902.00506`
[2] `lichess.org`

total of 1 billion games. These games capture a wide range of player skill levels (from beginners to grandmasters) and time limits (from 1 minute "bullet" games to 15-20 minute "classical" games). Each game is saved in the well-established PGN format, which can be parsed by existing Python or Julia libraries. Further, the PGN files are annotated with data about the game clock and a bot's evaluation of the position.

Chess is also attractive because it has a breadth of existing bots, and these bots could help to encode most of the domain-specific knowledge in this problem. For instance, the chess engine Stockfish may prove to be a helpful tool in this project: rather than simply suggesting the best move, it can output a list of moves sorted by their quality. Thus, it might be possible to simply build a model that predicts whether players will play a good or bad move in each position, but rely on Stockfish to determine what these moves are.

- **Hanabi:** A relatively small online community has developed around Hanabi[3]. This community has developed a set of playing conventions, in an attempt to learn how to play the game optimally, and an interface to play the game online, with roughly 50,000 replays recorded. The community is also supportive of developing and simulating new strategies. Together, this setting makes for an interesting supervised learning problem: learning the heuristics and conventions that players use during the game by simply observing their actions.

[3] `https://hanabi.live/`