**PokerPrime Project Proposal**

Team: Richard Aguilar, Adam Samulak, Tony Chow

The aim of our group is to learn how to design a neural network for poker. We will design three different neural networks one per member. In the initial stage we will focus on the basic implementation of a neural network in the poker game setting. Throughout the development process we will hold meetings in order to update and help each other. With initial neural networks designed we will shift to modifying them. Each member will focus on changing his algorithm with one strategy in mind. During the whole process our agents will be trained and tested in order to assess our progress. At the end all three algorithms will be evaluated and compared to the data available in the literature. If time permits we will use our experience to improve our networks and test them again. The final stage of our project will involve creation of a visualization for the project evaluation. We would like to create a front end simulation that can be used in our demo. However, if we don’t reach that stage we will use the built-in RL Card visualization. We will hold weekly meetings after our CSCI 353 class.

Member’s role:

Adam, Richard, Tony: Figure out how the interface of RL cards works. Use TensorFlow to design and build three different neural networks with minimal collaboration, outside of sharing general knowledge and usage. Upon gaining familiarity with TensorFlow we can create neural-nets each fitting different strategies, e.g. betting or preserving chips.

Since this will be a poker game, there is no dataset required. Instead, our agent will learn through self-play.

Timeline:

- 10/12: Project proposal due
- 10/20: Preliminary exploration of RL Card library, with focus on understanding the structure of the API. This is a crucial step to understand how to integrate our future algorithm with the RL Card library. It is critical for all members to understand it because the whole project will be built upon it. If the library proves to be too challenging we will adjust our plans accordingly.
- 10/27: Implementation of a basic neural network (using TensorFlow). Review literature that discusses the best practices to maximize effectiveness of neural networks. Review the poker game and most common strategies used.
- 11/3: Finalize our first general algorithm. Discuss possible modifications for focusing on strategy modification.
- 11/9: Implement strategy oriented algorithms and document our method.
- 11/16: Continue or work on our algorithms. Assess how we will train our agents.
- 11/24: Train and test each of our neural networks against one another for evaluation
- 12/8: If time permits, a front-end web application can be built to help with visualization.
- 12/11: Project due

Exhibit a live play between two agents and a play between an agent and a human. We will use basic Python itself for the visualization, however if time permits, a web application can be built. The logic could be built in JavaScript with HTML/CSS libraries to help visualize the game. The web application will have both a front-end and a back-end. The back-end being the machine learning algorithm we have implemented from scratch.

Each agent will be evaluated by: total winnings, VPIP and PFR.

- Total winnings will evaluate the effectiveness of the particular agent.
- Voluntarily put $ in pot (VPIP): percentage of the time that a player voluntarily puts money into the pot, with the chance to do so.
- Preflop raise % (PFR): percentage of the time that a player put in any raise preflop, with the chance to do so.

VPIP and PFR helps to classify agents into different categories that suggest the strategy an agent is using.

We will use milli-big-blinds per game (mbb/g). Average winning rate over a number of hands, measured in thousandths of big blinds. Win rate will be the other measure that will be used to evaluate our agent. It will be used in both situations against a human player and artificial agent.

1. Moravčík et al. (2017). DeepStack: Expert-Level Artificial Intelligence in No-Limit Poker *Science* 356, 508–513. https://science.sciencemag.org/content/356/6337/508

2. Vaswani et al. (2017). Attention Is All You Need. *arXiv* 1706.03762.

https://arxiv.org/abs/1706.03762