Research Continuation Proposal for Peterson Graph Game Project:

Where we left off:

We currently have an inkling that our Petersen graph has strategy as defined from our work at the MAA 2024 March Conference. Our methodologies include having a basic Q-Learning Agent play over many games against a random player. Since our agent won the majority of the games against this random player, we conjecture that the Petersen graph may have strategy. Now, our goal is to combine both Reinforcement Learning with formal mathematical proofs and produce finalized results.

Discussed targets for the semester:

As discussed in April, our goal is now not to move toward a conference but rather a Journal publication. Further, this project will now be part of the Belhaven Honors College commitment I have currently. Honors requires a paper by the end of the semester. Thus, it is my belief that the goals, to be listed later, are attainable during this Fall semester. Also, since we are no longer targeting an undergraduate conference but rather a journal and honors college, there are no longer restrictions on your contributions, and you are now able to work more closely on the research this go around. Further, your ideas of the strategy coefficient, etc. can be implemented into this coming paper if you are up for the challenge. With these targets in mind, let’s move on to the actual research changes and focuses for this coming semester.

Statement of Research Goal:

The goal of this research is to exemplify a viable method of foreseeing proof results using Deep Q-Learning from Demonstrations (DQfDs). For our paper, we will use DQfDs to demonstrate an exemplified strategy and define a class of graphs. We will use this DQfD model to play on larger graphs and produce winning results that would otherwise be unattainable to train on given state-space complexity and memory limitations. We will then formalize a proof that will show that our model was correct in forseeing strategy on the graph. This will then show the viability of DQfDs for mathematic proofs. The goal is to show that for induction proofs, we can use DQfDs to test out seemingly complex environments and guide the mathematician to a desired goal more efficiently.

Goals expanded:

* Generate the optimal strategy from the minimax algorithm
  + The minimax algorithm is a mathematical proof that if a game is a zero-sum game, it will have strategy. This will come handy in the future
* Use the optimal strategy given from minimax to train our model on smaller graphs on our class
* If minimax does not prove viable, we will then move to generating viable moves from Q-learning or Reinforcement Learning
* Use transfer learning to expand our DQfD model to be able to play on graphs it was not trained to play on
* Get results from this algorithm over graphs size 5, 10, 15, 20, 25, 50, 100, 200, 400, 500, 1000, 2000, 3000, 4000, 5000, 10000, 20000, 30000, 40000, 50000, 100000, 200000, 300000, 400000, and 500000
* As these graphs get arbitrarily larger, we show that there still exists strategy
* We then formally prove our game has strategy and/or is a zero-sum game
* If we can prove the game is a zero-sum game, we can show that the game is not one of random play

Explanation of terms:

Deep Q Learning from Demonstrations – a Reinforcement Learning technique developed in 2015/2016 that uses expert demonstrations to expedite the learning process. See the attached academic paper for more context. I can also discuss this further when we meet.

Transfer Learning – creating a model to perform tasks that it was not explicitly trained on. It takes knowledge from one domain and applies it to a different domain.