My current proposal is a variation of the minimum effort game. For my iteration, instead of the payoff being determined by the minimum effort put forth by all the participants, it will instead be determined by the minimum effort put forth by all participants **in range**. In this instance, in range refers to being within n degrees of separation, with the degrees of separation being variable across various different models. This is meant to model the travel of information across graphs of different sizes and with varying degrees of links. Additionally, it can help show the impacts of a few poor decisions unfolding into large scale welfare loss over time.

My model will be mainly computational. I plan on using the python programming language to create an agent based model to make decisions on what effort to put forth over several rounds. The crux of the model randomly generates graphs with completely randomized links. All individual agents will then randomly select an effort to begin the game, with heavy weightings placed upon the larger numbers. Then, several iterations of the game will be played continuously, with both individual and group welfare being recorded throughout the game. This model will include an algorithm that incorporates information that each agent has gained from the previous round, with some sort of decreasing weighting as the rounds progress. This function that determines this weighting will be able to be dynamically changed. This “learning” can be seen as a measure of the transmission of information across links, as through the links that each agent has they gain information about how to better “optimize” their future decisions. It is of notable importance that the “range” of the minimum effort game and the “range” of the learning data do not necessarily have to coincide for our model. This misalignment can help us analyze additional situations in where there may be over information (in the case that the range of the learning data is larger than the range of the minimum effort, in which the agent will be taking into account welfare data on agents that do not actually have an opportunity to impact their game) and partial information (the case in which the range of the minimum effort game is larger than the range of the learning data, making it hard to know exactly how many people chose “low” in an effort to adapt their range for future rounds). Additionally, there can be changes made to cost and payoff functions to view if changing differences between cost and payoff radically alters behavior and future predictability.

Because the data and decisions are being created “algorithmically”, I felt it was important to include randomness into decision making that would make it more inherently “human”. The minimum effort game computationally played by computers meant to optimize profit and with the knowledge that they are also playing with other perfectly optimized computers makes the data rather stale and pointless. I also considered the possibility of playing a large number of computer subjects alongside a handful of human subjects. This may prove useful to find out if the computer's algorithm is exploitable through some strategy, or if the inherent randomness creates an interesting strategic uncertainty for the human player to solve.

Effectively, I am looking to explore how the increase and decrease of freedom of information changes the speed and results of this “localized” minimum effort game. As the range of all individual agents increases, so does their information, and the impact of their decisions upon others. The minimum effort game is traditionally played with full information in every single round. By altering the amounts of information in a network setting, you can somewhat simulate how information travels across links and alters decision making from nodes that would previously not interact with each other.