Segregation Modeling

EECE7065 — Homework 2

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1 Random and Social Policies

Methodology

We implemented two segregation policies using the Schelling model. In summary, an L x L grid is initialized with N agents, with each agent being either blue or red. Each agent is happy if it has k matching neighbors. For our simulations, we used $L = 40$, $N = 1440$, and $k = 3$. The simulation consists of 30 simulations, each having 20 epochs. For each epoch, the population of agents is shuffled, then each agent is given the option to move. If the agent is happy, it does not move.

The first policy for the Schelling model is the random policy. In this policy, an agent decides its move simply by picking a random cell which will make it happy. If the agent checks 100 cells and none of them make it happy, it chooses the one with the most matching neighbors out of those 100 cells.

The second policy is the social network recommendation policy, or the social policy for short. At the beginning of each iteration, each agent is assigned n friends, which remain constant throughout the iteration. Each friend searches around it in a p x p grid for cells which will make the agent happy, then the agent chooses randomly from those cells. If no cells are suggested, the agent does not move.

The social model was used with varying values for n and p, and those results along with the random model results are shown in Figure 1.

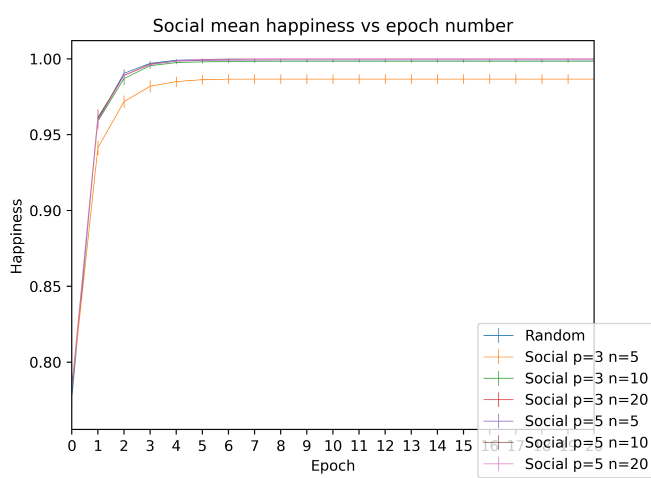

Figure 1: Time-series plot of average happiness for each epoch of the social policy compared to the random policy.

Discussion

The results shown in Figure 1 illustrate that random policy is able to converge faster and more consistently to an optimal happiness (happiness = 1.0) when compared to social network recommendation. Additionally, we can observe that a small number of friends ($n = 5$) and neighborhood ($p = 3$) results in the agents converging to sub-optimal happiness. We believe that this may be due to the fact the agents in the social network are dependent on the recommendation of friends to move. If there are too few friends and a small neighborhood, then the search space for available locations is much smaller and the agent may get stuck in an unhappy location. There is no mechanism in this policy to introduce randomness to the friends list, so the agent is stuck unhappy. Additionally, as more agents converge to a happy location, the friends and their neighborhoods become fixed increasing the chances that an agent may not be able to find an available location through friend recommendations.

2 Exclusive Social Policy — Wayne

Methodology

In the social policy, we noticed that some of the policies with lower n and p values converge to noticeably lower happiness levels, shown in Figure 1. To counteract that, I thought it would be interesting to make agents only able to be friends with their own color. The rationale is that if the agents are segregating, then a friend of the same color as the agent will be more likely to be surrounded by its own kind, so making all of the friends the same color should increase the likelihood of finding a cell that makes the agent happy.

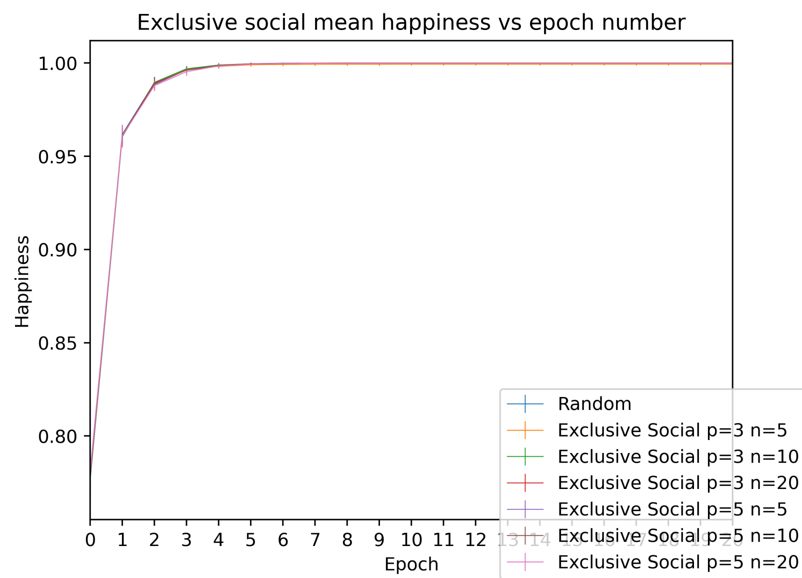

Figure 2: Time-series plot of average happiness for each epoch of the exclusive social policy compared to the random policy.

Discussion

The results show that the exclusive social policy is more effective at converging to all agents being happy. There is some slight variation in the first several epochs, but around epoch 5 all configurations appear to be mostly converged to 100% happiness, or slightly less. Note that $n = 3$, $p = 5$ still has small error bars, meaning that in some cases it converged to a state where not all agents were happy. This result is an improvement over the previous social policy, however it still suffers from the inability to change things up if it reaches a state where some agents are unhappy and do not have any suggestions from its friends.

3 Distance Weighted Random Policy — Liu

Methodology

In Policy 1, the selection of the random relocation treats all candidates equally. This alternative rule modifies it such that agents move to the best empty position regarding its matching neighbors weighted by the Euclidean distance from the agent. The selection poll is still a random p-size subset of the empty cells. The Euclidean distance also considers the environment wrapped to find the shortest distance possible.

To implement this policy, a weighted happiness index $h = w\left(\frac{d}{D}\right) \cdot \frac{n}{8}$ is used to evaluate the empty cells instead, where d represents the distance between an agent and an empty cell, w is a weight function, D is the maximum possible distance in the environment (the diagonal distance), and n is the number of matching neighbors.

I experimented with four types of weight functions: $w_{C1}(x) = 1-x$, $w_{C2}(x) = (1-x)^2$, $w_{F1}(x) = x$ and $w_{F2}(x) = x^2$. These functions vary in linearity as well as whether they weight close cells or far cells more.

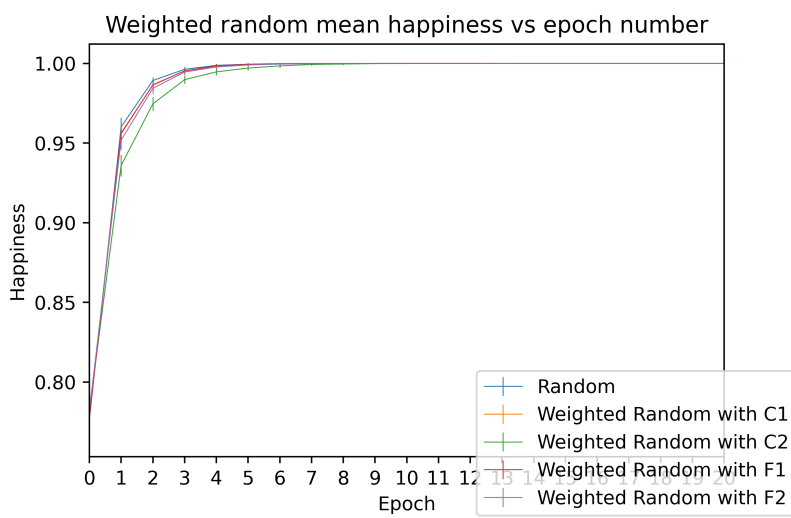

Figure 3: Average happiness of weighted random compared to Policy 1.

Discussion

Though they all eventually converged to 1, the performances of C1- and F1-weighted random policies are slightly less that that of equal randomness, followed by F2 and C2. In conclusion, using distance-weighted measure in the random move policy is not much better than treating all candidates equally. For a poorly-designed weight function, it may even result in lower efficiency.

4 Disposable Friend Policy — Sid

Methodology

In Policy 2, social network recommendation, we noticed that a smaller number of friends (n) and neighborhood (p) resulted in sub-optimal happiness (happiness < 1.0) as shown in Figure 1. This may have been due to the fact that if no friend can recommend a location, then the agent does not move. This may result in no available relocation for the agent as the search space decreases due to a low number of friends and small neighborhood. To counteract the friend recommendation bottleneck, I allowed each agent to select a new set of friends if the agent was unhappy and the friends were unhelpful. By selecting a new set of friends which guarantee an available location, the agent would not be stuck in a location which would make it unhappy.

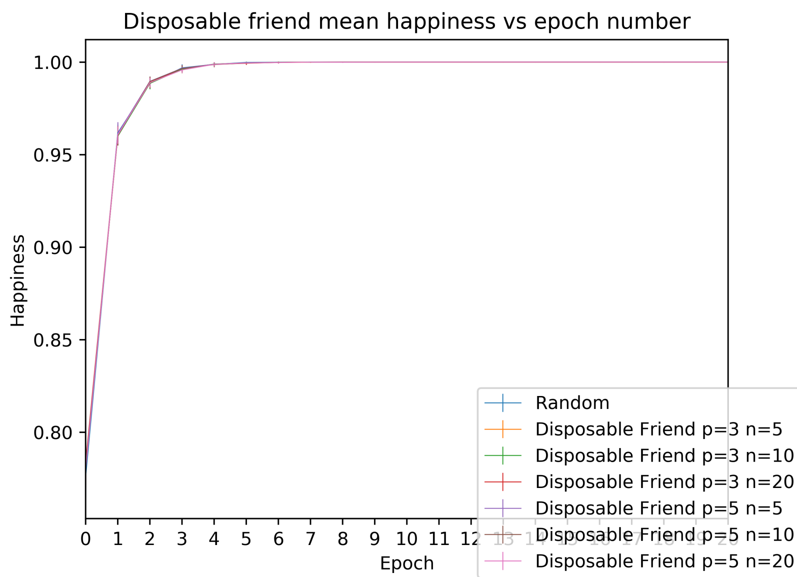

Figure 4: Time-series plot of average happiness for each epoch of the disposable friend policy compared to the random policy.

Discussion

The results shown in Figure 4 illustrate that the disposable friend policy was as effective as the random policy in converging the agents to an optimal happiness for all n and p values tested. This result is an improvement over the social network recommendation policy which results in sub-optimal convergence for low n and p values. The disposable friend policy performs similar to the random policy with smaller n and p values by resetting the friends when agents are unhappy and unhelped.