Persistent Inequalities in Society

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Abstract

Under what conditions do inequalities within society emerge? To explore this question we modeled the evolution of unequal distributions of wealth and social capital within artificially constructed societies. In order to better understand the causative factors of unequal wealth distribution, we examined and extended the NETLOGO Wealth Distribution Model made by Michael Gizzi, Tom Lairson and Richard Vail. We found the NETLOGO model to be incomplete in its ability to take into consideration the importance of the interactions between individuals in the development of social inequity. As a result, we also developed a MATLAB model for simulating the evolution of social contact networks. Taken together, these models identify several key factors that modulate the evolution of inequality within societies.

Keywords: inequality, networks, multi-agent, NETLOGO, Gini coefficient

Introduction

In our project, we are developing several models that are designed to help us understand not just why inequity persists within society, but also how it evolves over time. Such an inquiry is important because it helps explains Pareto's Law in which the rich in society, though few in number, tend to get richer while the poor [many, in comparison] tend to get poorer. Such queries, if fruitful, may prove useful in advising policy decisions, which aim to reduce the negative effects of huge disparities in wealth and power within society.

Our project is conducted as a two-part analysis of wealth distributions within society:
Part 1: NETLOGO simulation of Wealth Distribution
Part 2: MATLAB simulation of evolving social contact networks.

The use of two models of social inequity comes out of the recognition of the fact that the notion of "wealth" has several disparate interpretations. In our first model, we give consideration to the notion of "wealth" as it refers to physical resources such as food, capital, or money. In our second model, we analyze the dynamics of disparities in wealth as it refers to social capital, namely, personal connections with in a society.

Part 1: NETLOGO Simulation of Wealth Distribution

Guiding Question:

What are the key modulators of wealth inequality within this model? Specifically, we ask:

•How does increased population density affects the distribution of wealth?

•To what extents do increases in an individual's capacity to see the topology of their environment affect global measurements of inequality?

•How do variations in the productivity of the landscape affect the inequality of the system?

Methods:

The NETLOGO model used in this project is an adaptation of Epstein & Axtell's "Sugars cape" model. In this model, independent agents navigate a non-homogenous landscape collecting grain ["wealth"] under variable conditions of population growth, field of vision, grain growth capacity of the landscape, distribution of productive landscape, and more. In order to survive, individuals must consume part of their accumulated grain [their "metabolism"]. We modified the rules of the original NETLOGO Wealth Distribution Model. The model we used to simulate wealth distribution was defined by the following set of rules:

•The model begins with all individuals having the same amount of wealth.

•Each person moves in the direction where the most grain lies.

•Each time tick, each person eats a certain amount of grain ["metabolism"].

•When their lifespan runs out, or they run out of grain, they die and produce a single offspring.

•Wealthy individuals can choose to establish settlements on productive land; the settler gets all of the harvest from the patch.

•When settlers die, the patch becomes open for settlement by another individual.

•For death by old age capture the old-wealth, transfer it to the new generation of individuals who share 50 / 50 with new siblings.

•Initially, all individuals are assigned random values of vision, and metabolism. The maximum values of such variables can be manipulated in the model.

•Inequality is measured by calculation of the Gini coefficient.

Results – Part I NETLOGO Simulation

The results of a NETLOGO simulation of an extreme example of a society demonstrating low population [n=2], large fields of vision [max = 15], agents with low resource consumption [metabolism = 1], land with maximum productivity [NUM-GRAIN-GROWN=15, PERCENT BEST-LAND = 25%], equal distribution of life expectancy [all agents live until age 56],

Figure 1. In this experiment, the maximum possible field of vision was sequentially increased. The other conditions [kept constant] were as follows: PERCENT-BEST-LAND =10%; GRAIN-GROWTH-INTERVAL=1; NUM-GRAIN-GROWN=4; NUM-PEOPLE slider = 250; LIFE-EXPECTANCY-MIN=1;LIFE-EXPECTANCY-MAX=83; METABOLISM-MAX = 15

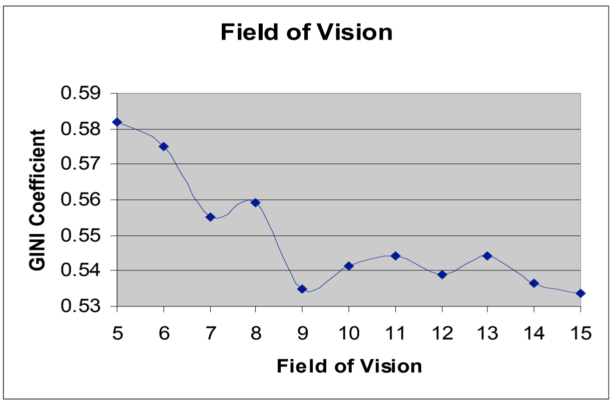


Figure 2. In this experiment, initial size of population was sequentially increased to simulate increasing population density. The other conditions [kept constant] were as follows: PERCENT-BEST-LAND =10%; GRAIN-GROWTH-INTERVAL=1; NUM-GRAIN-GROWN=4;MAX-VISION= 9; LIFE-EXPECTANCY-MIN=1;LIFE-EXPECTANCY-MAX=83; METABOLISM-MAX = 15

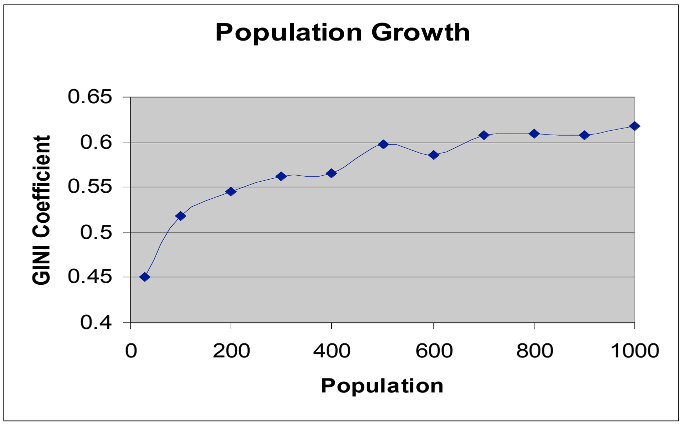
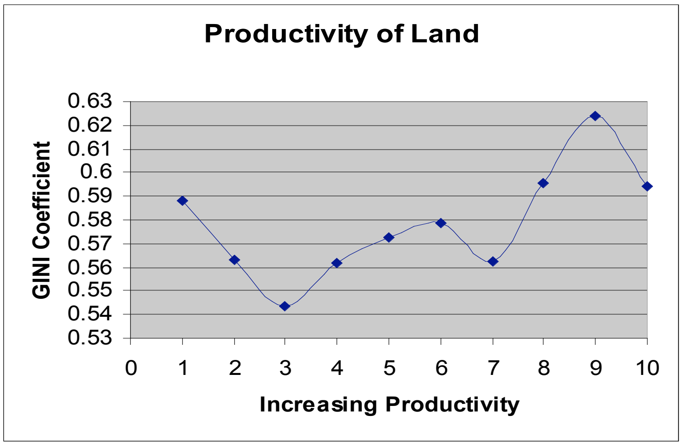


Figure 3. In this experiment, the NUM-GRAIN-GROWN variable was sequentially increased to simulate increasing productive capacity of the landscape. The other conditions [kept constant] were as follows: PERCENT-BEST-LAND =10%; GRAIN-GROWTH-INTERVAL=1; NUM-PEOPLE= 250;MAX-VISION= 9; LIFE-EXPECTANCY-MIN=1;LIFE-EXPECTANCY-MAX=83; METABOLISM-MAX = 15



Conclusions/Discussions – Part 1•

Cursory examination of the data show that increases in all individuals' fields of vision decreases inequality as measured by the Gini coefficient.

• Increasing population density results in increasing inequality.

• The relationship between increasing production of resources and inequality is unclear. It is possible that Simon Kuznets' theory that inequality increases over time, then at a critical point begins to decrease may explain the data obtained.

Analyses of extreme examples of the model are helpful in understanding the most potent factors affecting inequality. Taken together, these experiments suggest that low population, individuals with large fields of vision, agents with low resource consumption, land with maximum productivity, equal distribution of life expectancy, and stable population growth would characterize a society with the lowest measurement of inequality.

Part 2: MATLAB simulation of evolving social contact networks

In modern societies equipped with advanced transportation and communication facilities, social interactions amongst people play an important role in determining an individual's social status and potential wealth. We borrow the phrase of "social capitals" and defined it as the number of social connections each individual has for the present study. In network terminology, social capital of a node corresponds to the node's degree of edges. We further hypothesize that a fundamental and important factor causing social inequality (in particular the unbalanced distribution of social capitals) is the individual's tendency to connect to people with more social capitals. In fact, we see this fundamental individual tendency for most people as the root cause of persistency of social inequality independent of society forms across history. We also acknowledge the reverse effect of social structure on shaping an individual's decision rule and would like to incorporate this effect into our study.

Guiding Questions

The Matlab model for simulating the evolution of social contact networks is for testing the following hypothesis.

We hypothesize that a fundamental and important factor causing social inequality (in particular the unbalanced distribution of social capitals) is the individual's tendency to connect to people with more social capitals.

Questions that we would like to answer regarding this hypothesis are

1. Under what kind of (micro-level) individual decision rules will an (macro-level) unbalanced society (i.e. a society with uneven social capital distributions) emerge?
2. How does the evolution of the social network affect individual decision rules?
3. What factors may alleviate social inequality caused by individual biases? Either on micro-level or macro-level.

Method

The way we are testing the hypothesis is by building an evolution model for social contact network using Matlab. In our simulation,

- Social capital will be modeled as degree of links each node/person has;
- Each node will also have an intrinsic quality (IQ) number with a normal distribution;
- An attractiveness value of a node (when forming connections) is defined as a weighted sum its IQ and degree of links (social capital);
- Approximately 1000 nodes are used for our simulation;
- The decision processes of nodes when making connections are modeled as being between two extremes: 1) the absolute rational beings who always connect to the most attractive neighbors available and 2) the totally irrational beings who always connect randomly;
- Neighbors a node are defined as those nodes who are with 2 to *n* links away from the node; n is defined as 2 for most of our experiments.
- There is also a simple death and birth model which will reset old nodes link when they become too old.

- Degree distribution, Lorenz curves and Gini coefficient will be calculated for each step.

By adjusting the percentage of rational and irrational nodes with population, we can investigate the first question raised above. We have finished the code of this part and is analyzing the results.

To tackle the second question, we will plan to build some kind of evolution model for the decision rules itself. This can be done with a model similar to autocorrelation or contagion network model, which simulate the propagation of ideas or social norms in society. In our case, we will try to build a model so each node will try to influence its neighbors' decision rules. This will mostly likely to be dependent on the network structure, which was in turn determined by the decision rules collectively. The dynamics of this closed loop should be interesting. We are working on the Matlab code for this part right now.

For question 3, we have not look at it yet, but hope to infer some directions to look based on the study of the 1st and 2nd questions.

Results – Part 2 Matlab Simulation

We present simulation results of three kinds of decision rule setup. The steps of evolution are 500. The number of nodes is 1000. Initial network connections are setup so that on average each node has 5 links. The degree distribution of the initial network is given in Figure 1.

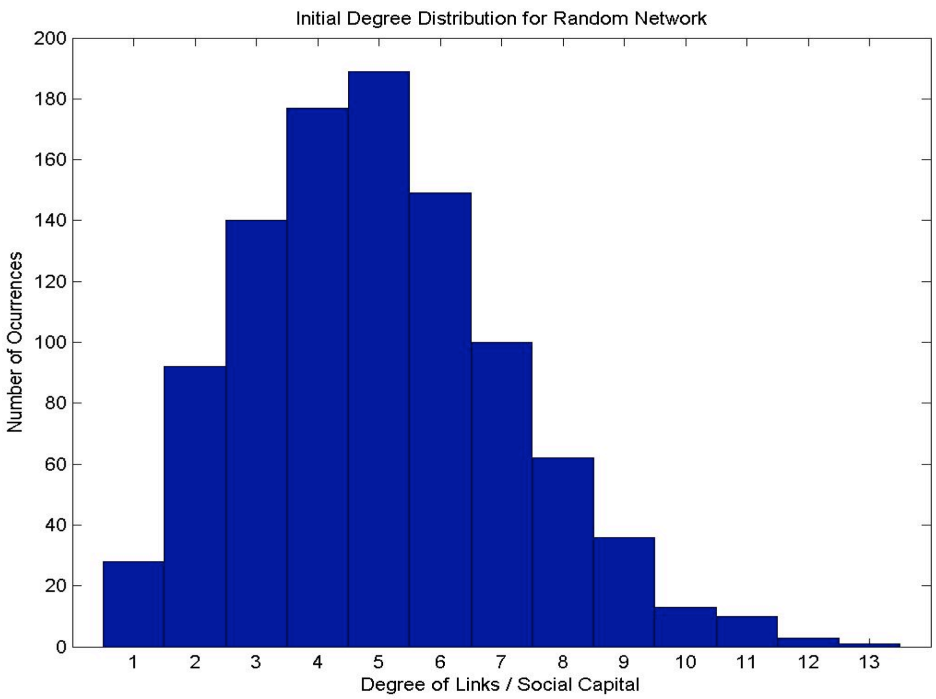


Figure 1 Degree Distribution for the Initial Random Network

After 500 steps of evolution, the final distribution for the degree of links are given in Figure 2 (for all Rational node case), Figure 3 (for all irrational node case) and Figure 4 (the case an uniformly distribution from rational to irrational among nodes)

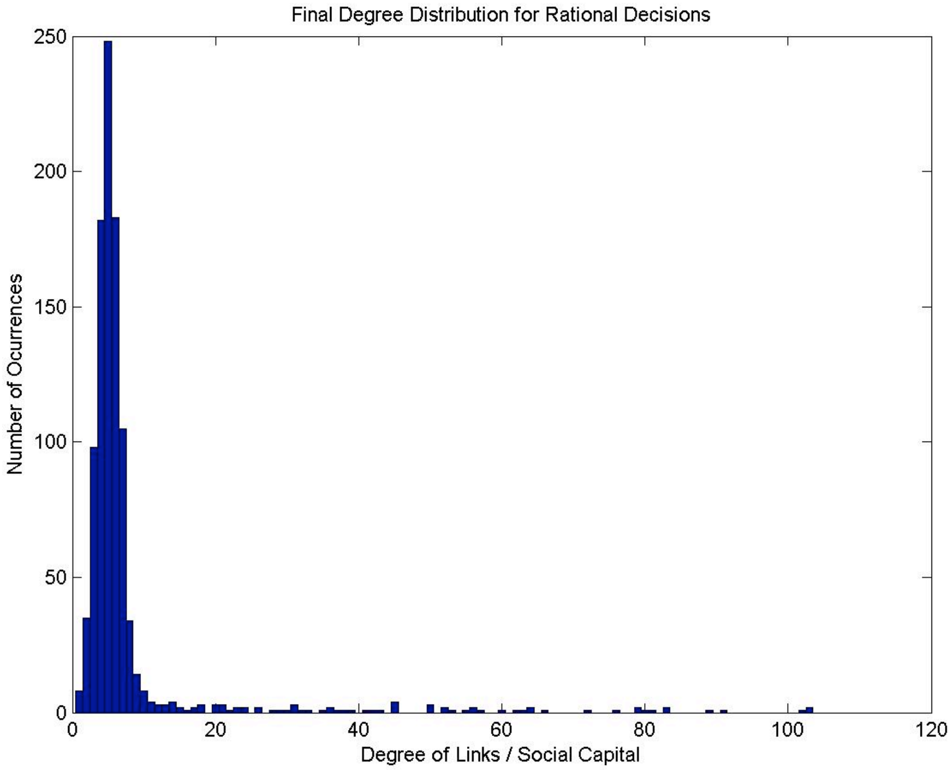


Figure 2. Final Degree Distribution When All nodes are Rational Makers

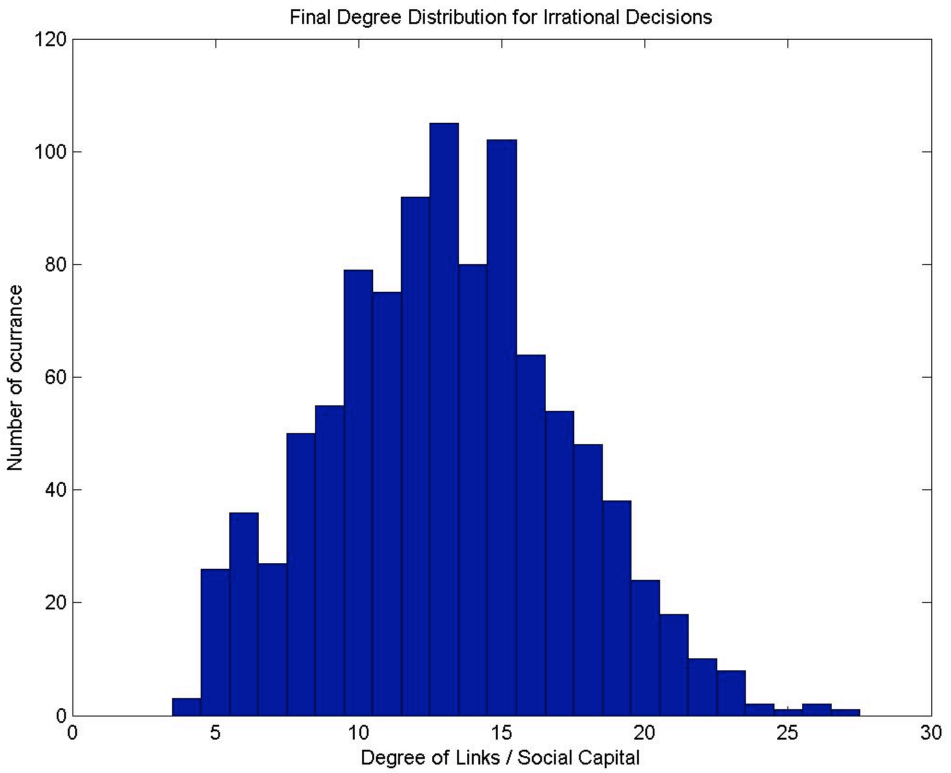


Figure 3. Final Degree Distribution When All nodes are Irrational Makers

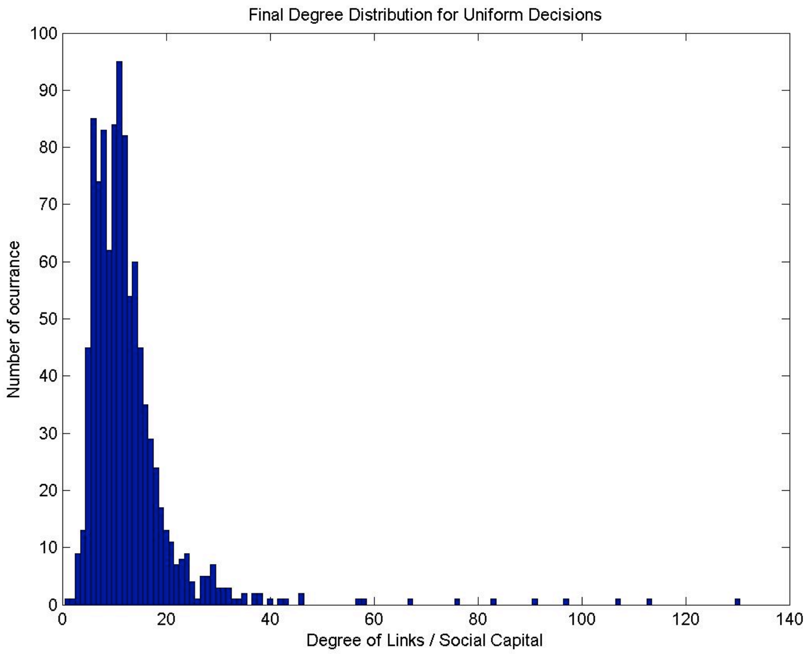


Figure 4. Final Degree Distribution When All nodes are uniformly distributed between Rational and irrational

The Lorenz curves are given in Figure 5 for a perfectly equal society (the 45 degree line), the initial random network (curve blue line), the final network for rational case (red solid line) irrational case (thick red line) and uniformly distributed case (dashed red line).

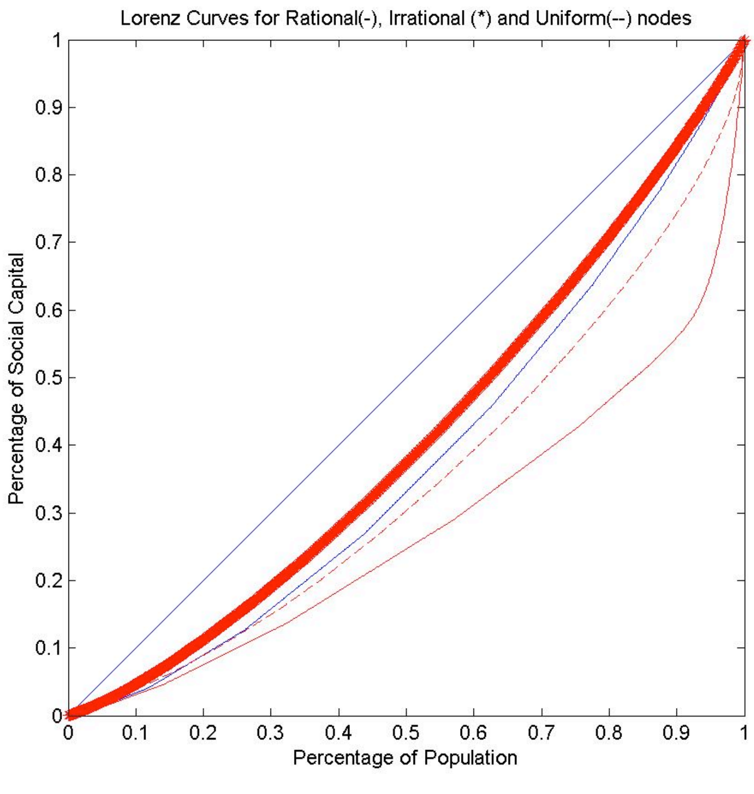


Figure 5. Lorenz Curves for different kinds of networks

Figure 6 gives the dynamical evolution of Gini coefficient over time (steps). Again, the solid line is for the rational case, the dashed line is for uniformly distributed case and the thick line is for the irrational case.

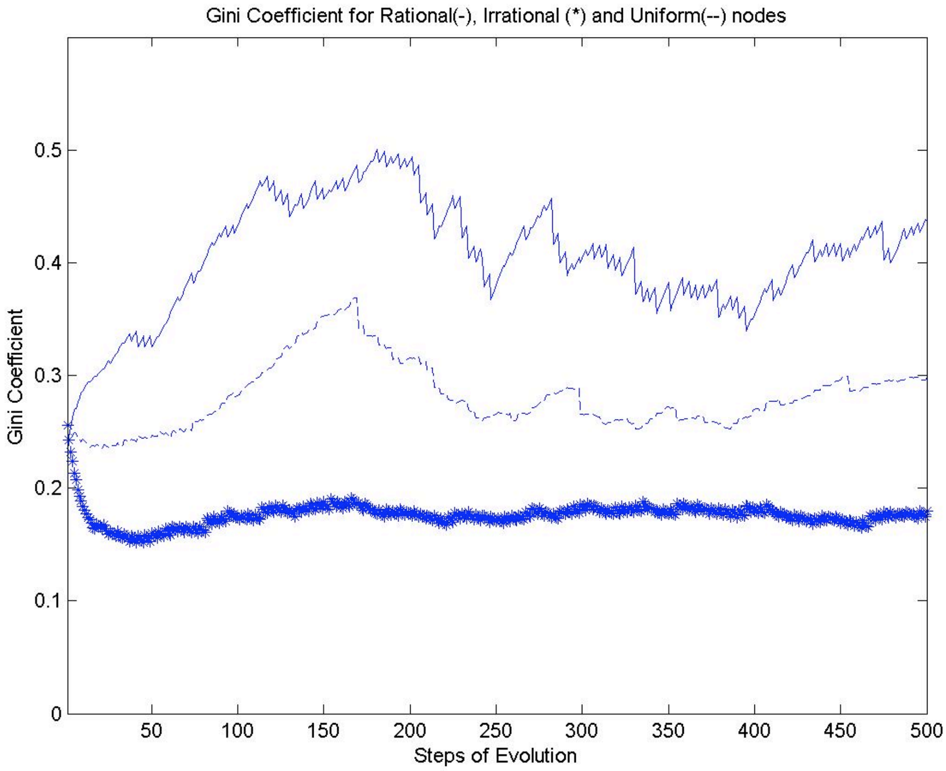


Figure 6. Evolution of Gini Coefficient for all three cases

Conclusions/Discussions – Part 2

Some observations and preliminary conclusions can be drawn from the simulation results shown above:

- For the three cases, it is clear that rational decision makers will cause social inequality for increase. This can be seen from the degree (social capital) distribution and also from the Gini coefficient plot and Lorenz plot. More quantitatively, after 500 runs, the Gini coefficient increased from approximately 0.25 to 0.43 for the rational case, decreased to 0.18 for the irrational case and roughly remain unchanged for the uniformly distributed case.
- The degree distribution changed from a bell shape distribution for the initial random net into a skew distribution with long tails for both rational and uniform cases. This signifies the formation of a small number of "rich people" in both cases. However, for the irrational case, the degree distribution remain unchanged as a bell shape curve with only the mean value increase from approximately 5 to 14.
- The results suggest that biased decision rules do result in more inequality than unbiased (random) choices. This is in agreement with the preferential attachment rule Barabasi found to be responsible for the generation of scale free networks []. The key difference is that the scale free network Barabasi simulated were formed with constantly adding new nodes to the network, while our network topology is form with an evolution rule for a constant sized network.

Extensions and Acknowledgment

The models used in the study are "exploratory models", according to the classification by Prof. Holland. However, we do believe that the simulation results and analysis presented here are highly relevant to the understanding of the urgent social inequality problem that persists over human history. We also acknowledge that our models are really primitive and inadequate. Many important factors affecting social inequality such as geography, heritage, history and money flows are not included. This project is a learning experience for us and we are grateful for the support we received from the CSSS organizers and fellow students.