UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

Colegio de Administración y Economía

Why is blood thicker than water?
An agent-based modeling approach to study the role of family links in the learning process in society

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An agent-based modeling approach to study the role of family links in the learning process in society

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RESUMEN

Se explora el papel que desempeñan los lazos familiares en el proceso de aprendizaje en una sociedad a través de un enfoque de modelamiento basado en agentes. Los agentes aprenden de un estado cambiante a través de observaciones ruidosas de dicho estado y señales recibidas de una red de familiares y amigos. Los lazos de amistad pueden ser seleccionados y romperse cuando dos agentes son demasiado diferentes entre sí, mientras que los lazos familiares no pueden romperse. La similitud entre dos agentes se calcula en función de su estimación del estado. Para evaluar el efecto de los lazos familiares, estos se pueden desactivar, lo que crea un modelo con solo vínculos de amistad. Un experimento diseñado para comparar ambas versiones del modelo muestra que la existencia de lazos familiares mejora las estimaciones del estado por parte de los agentes.

Palabras Clave: modelamiento basado en agentes, economía institucional, familia, modelamiento de redes, aprendizaje social, auto-engaño.

ABSTRACT

The role family links play in the learning process in a society are explored through an agent-based modeling approach. Agents learn from a changing state through noisy observations of said state and signals received from a network of family and friends. Friend links can be chosen and break when two agents are too dissimilar from each other while family links cannot be broken. The likeness of two agents is calculated by using their estimation of the state. To assess the effect of family links they can be turned off creating a model with only friend links. An experiment designed to compare both versions of the model shows that the existence of family links improves the agents' estimations of the state.

Keywords: Agent based modeling, Institutional economics, family, network modeling, social learning, self-deceit.

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INTRODUCTION

This study tries to shed light on a possible origin of the family institution. The hypothesis is that family links have an advantage over friend links because, as opposed to friend links, they are not chosen. Since they are not chosen, families can be internally less similar than friend groups. This in turn could lead to better choices made by individuals who have links that were not chosen and are hard to break. Hence, this paper tries to find if there could be an institutional reason for family links to endure that could benefit society.

To be clear, I am not referring to parents raising children or couples getting married, but cousins staying connected, or children visiting their parents years after they have left their family home. People do not choose who their parents, cousins or daughters are, but they keep familial links. I will argue that a possible reason for why families stay together is, at least partially, because there is a practical advantage in having a family. I will also argue that this possible advantage stems from the fact that family links are not chosen and are harder to break than friend links.

To argue my hypothesis, I used agent-based modeling as my methodology. I made a model in which agents receive signals both from friends, links that can be chosen and broken, and from family, links that are not chosen and do not break. Then I employed an experiment that allowed me to compare how agents performed learning about a state, with and without family links. The agent-based modeling methodology allowed me to look for a theoretical mechanism through which the family institution could have practical and non-obvious social benefits.

The mechanism I look for has to do with what Adam Smith wrote on the *Theory of moral sentiments* about self-deceit. Smith thought people act immorally because we cannot see our actions, the same way others, and society in general, see them. Immorality begins when we accept our own partial view of our actions (Smith, 2002). In other words, we convince ourselves that we are not evil by ignoring the judgment of others.

Smith believed that self-deceit could be remedied by interacting with others. Socializing and, more specifically, being judged by others can remedy the ill effects of self-deceit. People act morally thanks to the sympathy they receive from others when their actions are judged positively. It is pleasurable when one’s actions are judged as appropriate, and painful when they are not (Smith, 2002). This leads to the conclusion that people will tend to associate with others that hold similar beliefs about morality or, in Smith’s terminology, moral sentiments. This could lead to a social form of self-deceit in which people only associate with others who will not negatively judge their actions.

Smith’s thesis has two important implications for the purpose of this paper. First, diversity in groups can lead to better choice making through curbing the effects of self-deceit. And second, people will choose their friendships according to similarities in beliefs, which will lower group diversity and lead to worse outcomes. However, this issue could be remedied if people could not choose who they interact with.

This paper aims to demonstrate that there is a theoretical mechanism through which the family institution could diminish the ill effects of self-deceit by not allowing individuals to choose all their social links. This would mean families play an important, non-obvious, social role in the learning and choice-making processes. This is a role that could partly explain the emergence and resilience of family as a social institution.

LITERATURE REVIEW

The model was built on a series of results by other authors that have shaped this paper's hypothesis and assumptions. The reviewed literature comes from a multidisciplinary set of sources centered around learning and diversity. This study aims to expand on previous work by considering differences between family and friendship links within social networks and their effect on diversity and learning.

Reaching Consensus, DeGroot's (1974) seminal paper, sets the basic premises for this paper's model. In DeGroot's model a group of agents tries to reach a consensus about a parameter by learning about each other's subjective opinion distributions about said parameter. However, this model does not consider if a real or correct answer exists, and no consideration to group diversity is explored. This paper serves as a starting point for further modeling of the social learning process, including this paper's model.

The findings of Hong and Page (2004) were helpful to take diversity into account. Once again in a modeled setting, the authors found that diversity in groups of problem solver agents had a significant positive effect on performance. It was found that diverse groups of problem solvers could outperform elite, but homogeneous, groups (2004). This model serves as a steppingstone for this paper's hypothesis. Diversity is good, so, can families increase group diversity better than friendships can?

To explore friendships and their potential for reducing diversity the empirical work of Banhs, Pickett, and Crandall (2012) is used. These authors observe that people tend to choose to establish friendships with similar persons. The bigger the pool of potential friends, the more similar the friend groups. This result points to friend groups not having much diversity, at least in large populations. In this paper's model friendships are formed randomly, but then are endogenously revised based on similarity between friends.

But the lack in diversity in friend groups is only half of this paper's premise; it is also necessary to look at diversity within families. The relevant findings come from behavioral genetics, and more specifically, twin studies, which allow to separate nature from nurture effects on behavior. Thus, they can be an effective way to find the effects of both genes and parenting on behavior. Of course, both genes and parenting are shared within most families so for this paper's hypothesis it is necessary that a significant part of behavior is not explained by genes or parenting, but rather by what the literature calls "unshared environment". If unshared environment has a large effect on belief formation, then it is plausible that families can have diverse beliefs.

To look at the effect of unshared environment the work of Alford, Funk, and Hibbing (2005) was reviewed. These authors use twin data to study the role family and genes play on political view formation. They find that the largest chunk of political views and beliefs comes from genes and unshared environment, while parenting has the smallest effect on most of the views and beliefs surveyed. With these results it can be sustained that there is some wiggle room to argue that families can in fact have diverse beliefs.

Finally, this paper uses the model by Dasaratha, Golub, and Hak (2018) as a foundation. It uses DeGroot's work as basis to model agents that use internal and external signals to learn about a changing state. The internal signal is a noisy observation of the state while the external signal comes from their neighbors. They found that signal diversity improves the agents' learning. This paper's model is a simplified version of Dasaratha, Golub, and Hak's model in which agents learn not from neighbors but from friends and family networks, and in which friendships can be broken and formed based on similarity while families do not change.

MODEL DESCRIPTION

To study the effects of links that are not chosen and cannot be broken in the learning process an agent-based model was designed using the Netlogo programming language. The full model code and GUI can be found in annexes A and B. Agents try to estimate a changing state using a private signal, a noisy observation of the state, and two external signals, the average estimation of their friends and the average estimation of their family. On each tick agents can change their friend network if the distance between their own estimation and one of their friends' estimations is larger than a preestablished tolerance variable (T). Each period the RMSE is calculated using the current real state and all agent estimations.

Table 1: model global variables

Variable Names	**Descriptions**
N	Number of agents in the population
S	Real state that agents estimate
$pFriend$	The probability that any two agents make a friend link
$pRelative$	The probability that any two agents make a family link
T	The tolerance agents have for changing friends

Table 2: model agent variables

Variable Names	**Descriptions**
E	An agent's estimate of the real state
M	An agent's friend set
F	An agent's family set
m	The number of friends an agent has
f	The number of relatives an agent has
RSE	An agent's error measured as the root squared difference between their estimate and real state
$Noise$	The amount of noise all the agents have on their observation of the state

The Model has N agents estimating state S, which changes every tick following a normal distribution. In the first tick (t=0) all agents start with estimate e_{0i} which is uniformly distributed among all agents. Every i agent has an e_{ti} estimate for each period. Friendships and family links are created following the Erdős-Rényi Algorithm. The only difference between the creation of family and friendship links is that every agent can only form one family link, while they can form an arbitrary number of friend links. Every period all agents update their estimate using the average of their own noisy observation of the state, the estimates of their friends, and the estimates of their family. Also, agents change friends following conditions that will be explained later in this paper.

The model starts at tick zero (t=0) in which the N agents are born. All agents start with a randomly assigned initial estimate e_{0i}. In this initial period every agent forms their family and friend links creating an Erdős–Rényi network. To create this network, variables $pRelative$ and $pFriend$ are used to make links randomly between agents. An agent can make an arbitrary number of friendships but only one family link. The reason for this adjustment will be explained further in the experiment section. Agents cannot make a family link with an agent they have a friend link with and vice versa.

The Erdős–Rényi network model was chosen because it simple yet power full. This allowed me to capture some of the nuances of real-world networks while keeping my model relatively simple. I also used Erdős-Rényi because it is considered a standard network model and a mostly neutral methodological choice (Barabási, 2016). Of course, using this network model does have some significant limitations that will be discussed further in the conclusions section.

Once every agent's links are created the model goes into the subsequent ticks (t>0). Every tick, all agents use $m + f$ (number of friends plus number of relatives) external signals plus their own internal signal to estimate the state ($e_{t,i}$). An agent's external signals come from two places: first the agent's friends' estimations, and second, the agent's relatives' estimations. This is why the number of external signals is equal to the sum of the number of friends and relatives an agent has. The internal signal comes from a direct observation of the current real state (S_t) plus random noise. Finally, an agent's estimate is updated using a simple average of all the signals.

$$e_{t,i} = \frac{1}{f_{t,i} + m_{t,i} + 1}\left(S_t + noise_{t,i} + \sum_{j=0}^{f_{t,i}} e_{t,j} + \sum_{k=0}^{m_{t,i}} e_{t,k}\right)$$

Where noise is a uniformly-distributed random variable.

$$noise_{t,i} \sim U$$

So, an agent's perception is equal to the average of their own private signal plus the sum of the estimates of their friends plus the sum of estimates of their relatives. It is necessary to mention that to calculate this update, the external signals are taken from the current estimates of an agent's friends and family. This means that the estimates taken for the external signals may or may not have been already updated in the current tick.

After all estimates have been updated, agents now revise their friend links. As said before, friend links can be broken, and for this the T variable is used. An agent i will update their friend list if and only if the following three conditions are met:

1) $M_{t,i} \neq \emptyset$
2) $\exists j \in M_{t,i} : |e_{t,j} - e_{t,i}| \geq T$
3) $\exists k \notin M_{t,i} : | e_{t,k} - e_{t,i}| < T \ \wedge \ k \notin F_i$

Where $M_{t,i}$ is the friends set of agent i in tick t and F_i is the relatives set of agent i. The first condition is simply that the agent must have at least one friend. The second condition is that there must exists an agent j in i's friends set and the difference between j's and i's current estimates must be greater than or equal to T. The third and final condition states that there must exists an agent k outside i's friends set, the difference between k's and i's current estimates must be greater than or equal to T and k is outside i's friend set.

If an agent i meets all three conditions, they will break their friend link with agent j and make a new friend link with agent k. These conditions ensure that the total number of friend links is constant. Note that the friend links of an individual agent are variable. The reason to make it so the total number of links is kept constant will be discussed further in the experiment section.

To evaluate societal performance every tick the RMSE is calculated. The RMSE in the model is defined as the square root of the average square distance between each agent's estimate and the real state.

$$RMSE_t = \sqrt[2]{\frac{1}{N}\sum_{i=0}^{N}(e_{ti} - S_t)^2}$$

EXPERIMENT

To draw conclusions from the model an experiment was designed using the behavior space tool from Netlogo. The experiment was designed to test if the existence of family ties resulted in better societal performance, i.e., if family links improved agents' learning of the state. Two simulations were run, the control one with the creation of family ties turned off through the $pRelative$ global variable and the test one with family links turned on. The variable values in the simulations were set as follows.

Table 3: experiment variables

Variable Name	Variable value
N	500
T	5
$pFriend$	0.04
$Final\ tick$	500
$pRelative$	$0\ for\ control, 1\ for\ test$
S_t	$\sim N(50,10)$
$e_{0,i}$	$\sim U(0,100)$
$noise$	$\sim U(-50,50)$
$maxTicks$	500

The values for $pRelative$ used were 1 and 0. These values were chosen so that in both simulations the total amount of links remained roughly the same making them more comparable. This is part of the reason agents can only form a family link once, so that when $pRelative$ is equal to 1 the total number of family links is equal to N, and the total number of links is more easily controlled. Also, when $pRelative$ is 1 it is guaranteed that every agent has at least one family link so that any effect these have is evenly distributed.

The value of $pfriend$ was set to 0.04 in both simulations. This value was chosen, again, to keep the total link number similar in both simulations. Since family links are created prior to friend links and a friend link cannot be formed with a relative, there is a negative correlation between $pRelative$ and the total number of friend links. The 0.04 value produces around a thousand friend links with $N = 500$ and $pRelative = 0$ while it only produces around 500 friend links with $N = 500$ and $pRelative = 1$. This makes 0.04 an excellent value to maintain the total number of links in the control and the test at around a thousand. If the total number of links varied too much between simulations, the effect of the total number of links could be confounded with the family links effect.

The $\sim N(50{,}10)$ distribution chosen for S_t makes it so the real state remains easy to use in conjunction with the $\sim U(0{,}100)$ distribution used for $e_{0,i}$ and $noise_{i,t}$. The $maxTicks$ variable value was chosen to ensure that the experiment would not omit any effect that only appeared after a given number of ticks. Each simulation was run a hundred times, then the results were taken from the average RMSE in the 500 ticks from each individual run.

CONCLUSIONS

When comparing the average RMSE from the 100 test simulations and the 100 control simulations the pattern showed in figure 1 was observed. All the test simulations have a lower RMSE than the control simulations, hinting at a positive impact family links had on learning in the model. To add robustness to the result I assumed that the RMSE is normally distributed and performed a t test on the average difference of the 100 test and control runs. The result is statistically significant at the 99% confidence rate.

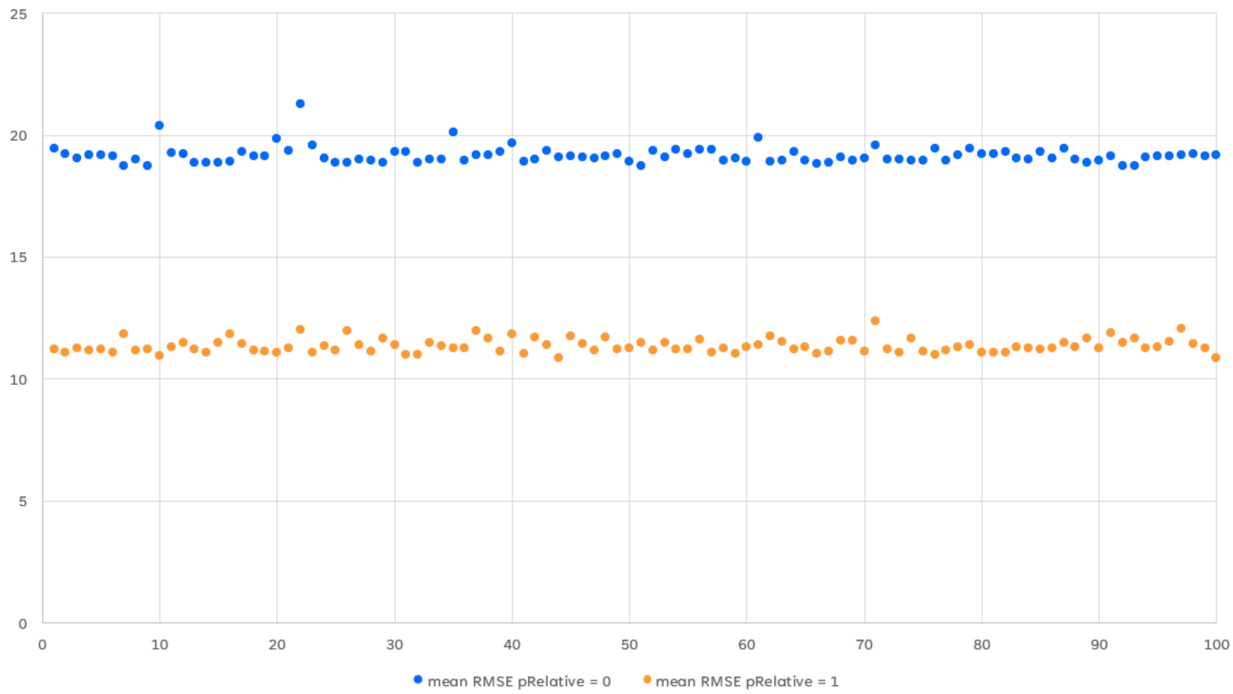

Figure 1: experiment results

This means that there is a mechanism through which family links can improve social learning. Since the only difference between family and friend links in the model was that friend links could be broken based on similarity, it can be said that diversity is at the center of the result. Family links can improve learning though increasing the diversity of the signals an agent receives from their friend and family networks.

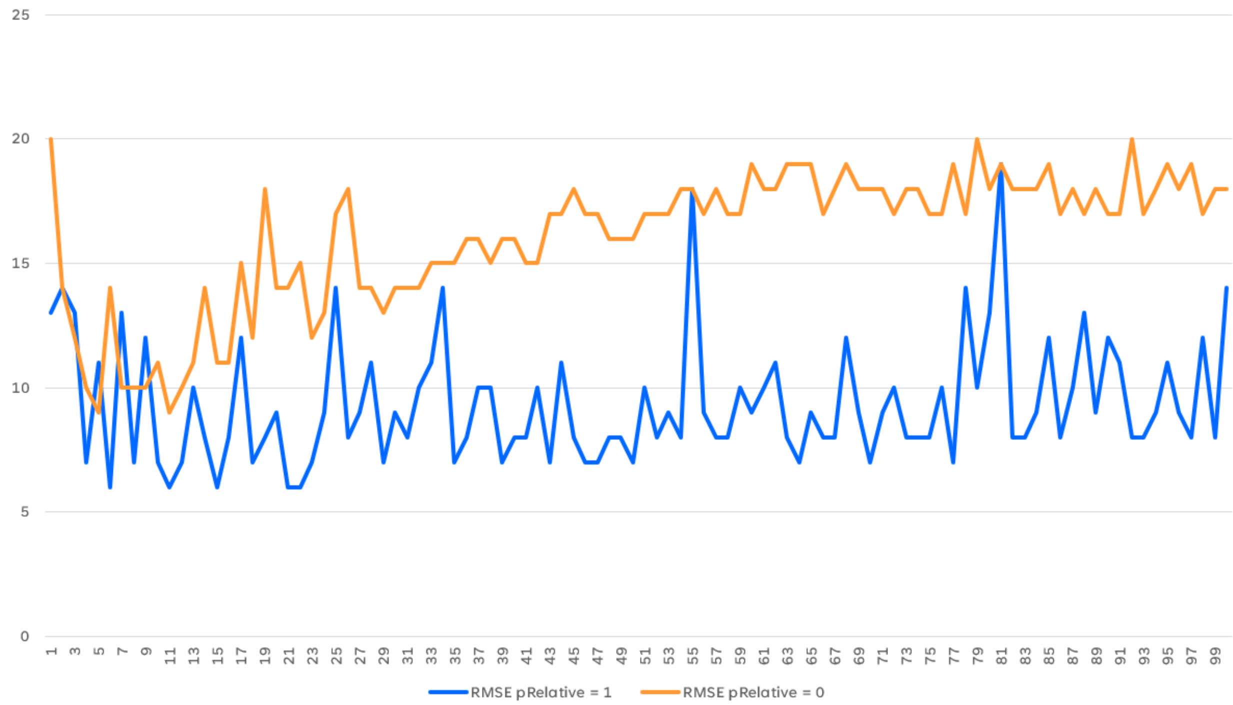

Figure 2: mechanism visualization

Figure 2 shows the RMSE in the first 100 ticks of two arbitrarily chosen runs. Around the fist dozen ticks both models show similar RMSE but, starting at tick 15, a clear difference between the two starts to show. While the simulation with family ticks turned on has a somewhat stable behavior, the simulation without family links shows a clear increase int the RMSE.

The increase in errors can be explained by agents changing their friend links according to similarity. As more agents change their friend links, the less diverse their network becomes. This leads to worse estimations of the state. Eventually, the link changing process stops and the RMSE stabilizes at a higher level. Meanwhile, the simulations that have family links never present any sustained increase in the RMSE. However, a question remains: family links appear to increase the RMSE's variance. The reason for this is not clear and should be further analyzed in a future study.

Also, the RMSE in the simulation with family links has a lot of dramatic increases from the mean followed by quick corrections. However, decreases in RMSE are not as large or frequent. Again, the reason behind this behavior is not clear. It is possible that the difference in the creation of family and friend links could be responsible for this and the higher variance in the simulation with family links; however, this possibility should be explored further in a future study.

This model and result suggest that family, as an institution, has a larger role in society beyond the obvious. Families could provide a source of diversity to the information an individual receives, thus improving communal learning and helping them make better choices of all kinds. The result can also contribute to understanding the success that family has had through history and why it is such a resilient institution in the modern world. This result sheds light on a potentially significant and interesting factor, the relationship between family and diversity, which could play a significant role in social learning.

The existence of this mechanism can serve as a potential explanation for the origins of family and its institutional functions. It is possible that family helps with social learning and choice making. Tying this back to Adam Smith´s ideas about self-deceit, the model shows a conceivable way in which families, by not being chosen by individuals, can reduce self-deceit and lead to better outcomes. However, the model does not give a definitive answer due to its lack of complexity.

The model does not aim to give a complete resolution but to serve as a first step in the study of the role of family links in social learning. It has plenty of limitations and the result is hard to interpret in a more realistic context. First, the state is very abstract, it can roughly represent several real-world social spectrums such as political views, fear of bank runs, and risk averseness to name a few. However, making S_t this abstract can be a double-edged sword. It can roughly represent anything, but it cannot thoroughly represent anything specific. In future studies a better way to model more specific spectrums could be helpful.

Secondly, the model does not take behavioral genetics results seriously enough. As said in the literature review section, a sizable portion of human behavior can be explained by genetic and nurture effects. The model, however, does not place any similarity between relatives. This could be making the believes of families in the model significantly more diverse than those of real families. It is necessary to include more realistic similarities within families to further evaluate this paper's hypothesis.

To address this issue, a future model with generations and mutations could be helpful. In said model, agents could choose couples based on similarity. Offspring would inherit some, but not all their parents' beliefs, using a mutation variable. This would make it possible to directly address the behavioral genetics results that my current model does not consider. Developing a generational model is a clear next step for this study.

The use of an Erdős-Rényi network model also poses some considerable limitations. As said in the model description section, this network model can capture some important nuances of real-world networks; however, it cannot be said that it accurately represents a real-world social network. The most important characteristics that Erdős–Rényi lacks are hubs and a variable distribution degree, which are present in most real-world social networks (Barabási, 2016). For future studies, a model that utilizes a more complex and realistic network is necessary.

The model can also be improved by adding more complexity, such as evolutionary pressure and weighted signals. Also, more complexity should be added to the link changes process, including a more realistic set of conditions to change friends or a second tolerance value to break family links, for example. More detailed types of links can be added such as paternal and fraternal links which could have particular characteristics based on behavioral genetics.

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ANNEX A: COMPLETE NETLOGO CODE

```
;Mateo Mena M.
undirected-link-breed [friendships friendship]
undirected-link-breed [families family]

Globals[
 N
 State
 errors
 tolerance
 noise
 relative
]

turtles-own[
 estimate
 SErr
 isFriend ;this variable serves to validate if an agent is part of another agent's friend set
]

to setup ;sets up global and agent variables
 clear-all
 reset-ticks

 set N 500
 set State random-normal 50 10
 set errors 0
 set tolerance 5
 set noise 50

 create-ordered-turtles N[
 set color white
 set size 0.8
 set shape "turtle"
 set estimate random-float 100.0
 set SErr (estimate - State) ^ 2
 set isFriend false
 set relative nobody
 set ycor random-ycor
 set xcor random-xcor
 ]
 set errors int ((sum [SErr] of turtles)/ count turtles)
 makefamily ;calls function that creates family links
 makeFriends ;calls function that creates friend links

 ask friendships [
 set thickness 0.1
 set color blue
 ]

end

to influence ;this function makes the social influence process happen

 ask turtles [
 set estimate (State + random noise - random noise + sum [estimate] of family-neighbors + sum [estimate] of
friendship-neighbors )/(count family-neighbors + count friendship-neighbors + 1)
 set SErr (estimate - State) ^ 2
 ]
```

```
 set errors int sqrt((sum [SErr] of turtles)/ count turtles)
end

to linkChanges ; changes friend links based on similarity and other conditions

 ask turtles with [not empty? [estimate] of friendship-neighbors][
 let friendlies other turtles with [abs( estimate - [estimate] of myself) <= tolerance] ;searches for potential new
friends

 ask friendship-neighbors[
 set isFriend true ;labels all the agent's friends
 ]

 if(any? friendship-neighbors with [abs( estimate - [estimate] of myself) >= tolerance] and any? friendlies with
[isFriend = false])[
 let badFriends friendship-neighbors with[abs( estimate - [estimate] of myself) >= tolerance ;searches for friends
to break a link with
 ]

 ask friendship-with one-of badFriends [
 die ; breaks link with one friend
 ]
 create-friendship-with one-of friendlies with [isFriend = false] ;creates a new friendship

 ask friendship-neighbors[
 set isFriend false ;resets all friendship labels
 ]
 ]
 ]
end

to makefamily ;creates an Erdos-Renyi network of relatives. Every agent forms a link once

 ask turtles with [ count family-neighbors = 0][
 if(random-float 1.0 < pRelative)[
 if (any? other turtles with [ count family-neighbors = 0])[
 set relative one-of other turtles with [count family-neighbors = 0]
 ]
 if (relative != nobody)[
 create-family-with relative
 ask relative[
 set relative myself
 ]
 ]
 ]
 ]

 ask families[
 set color red
 ]
end

to makeFriends ;creates an Erdos-Renyi friends network, validates so relatives are not friends

 ask turtles [

 if(family-neighbors != nobody)[
```

```
 create-friendships-with turtles with [
 abs( estimate - [estimate] of myself) <= tolerance and
 not family-neighbor? myself and
 self > myself and
 random-float 1.0 < pFriend]
 ]

 if(relative = nobody)[
 create-friendships-with turtles with [
 abs( estimate - [estimate] of myself) <= tolerance and
 not family-neighbor? myself and
 self > myself and
 random-float 1.0 < pFriend]
 ]
 ]
end

to go ;starts tick counter calls social influence and link changes methods
 if(ticks >= 100) [stop]
 influence
 linkChanges
 set State random-normal 50 10

 ask friendships [
 set thickness 0.1
 set color blue
 ]
 tick
end

to-report stateReporter
 report State
end

to-report errorReporter
 report errors
end

to-report friendshipsCountReporter
 report count friendships
end

to-report familiesCountReporter
 report count families
end
```

ANNEX B: NETLOGO GUI