The Ascape Model Developer's Manual

Damon Centola

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Preface.

This manual was developed during the summer of 2002 at the Center for Social and Economic Dynamics at the Brookings Institution. The manual reflects the need for an introduction to agent-based modeling that serves the general social science community, and that also highlights the usefulness of Ascape for scientific research. Although agent-based models (ABMs) are equally useful in the biological and physical sciences as they are in the social sciences, methodological difficulties in the social sciences have motivated the widespread appeal of agent-based modeling. In recent years, agent-based modeling has become an increasingly important tool for modeling human social behavior. The consensus among its proponents is that, in comparison to traditional analytic techniques, agent models can better represent human social life because of their facility for modeling heterogeneous agents, bounded rationality, out of equilibrium dynamics, and agent-agent interactions within social networks.

I developed this manual while I was a doctoral student in Philosophy at Johns Hopkins University. My introduction to agent-based modeling came from evolutionary biology, and my long-standing interest in the evolution of altruism and problems in group selection. My research has since broadened, understandably, to include many problems in social science. Recently, I have been working on the role of group selection dynamics in the formation of social institutions.

This manual has benefited from extensive discussion with the inventor and developer of Ascape, Miles Parker, as well as from helpful comments from Josh Epstein and Peyton Young, and from the continued guidance of Rob Axtell. The manual has also benefited from earlier articles outlining the structure and use of Ascape. These articles include:

Parker, M. 1999. "Ascape: an Agent-based Modeling Environment in Java", Proceedings of Agent Simulation: Applications, Models, and Tools" University of Chicago.

Parker, M. 2000. "Ascape: Abstracting Complexity" Swarmfest 2000 Proceedings, forthcoming (Brookings Website)

Parker, M. 2001. "What is Ascape and Why Should You Care?", *Journal of Artificial Societies and Social Simulation* vol. 4, no. 1. http://www.soc.surrey.ac.uk/JASSS/4/1/5.html

-Damon Centola

Special Note.

I'm extremely grateful to Damon Centola for writing a manual that is both thoughtful and practical, and that captures the essence of the Ascape approach. Damon wrote this manual five years ago, and since that time Ascape has changed in subtle but significant ways. In preparation for the open source release of Ascape, I've attempted to update the code examples so that they will work with the released version. In a few places I have updated the text to reflect changes and improvements, and I hope Damon will excuse any inconsistencies that my slight revisions may introduce.

-Miles T. Parker
September, 2007

About Ascape.

This manual is included as a part of the Ascape model development package. Ascape was originally developed at the Brookings Insitition, subsequently improved and extended at Bios Group and NuTech Solutions, Inc. and has now been released under a BSD Open Source license. Ongoing development and maintenance is provided by Metascape, LLC, Brookings, NuTech Solutions, Inc., and others. No endorsements of any organizations or products by any other organization is implied or intended.

Ascape was developed for the Java platform and can run on any contemporary computer system. For a copy of the latest release of Ascape, please visit ascape.sourceforge.net.

This is the complete text of the Ascape license:

Introduction.

An Overview of the Ascape Model Developer's Manual

This manual is an introduction to agent-based modeling using the Ascape Modeling Framework. This framework is a set of Java classes that allow a developer to easily create collections of agents and assign these agents rules for interacting on a spatial lattice or in a network. The framework is also designed to allow the developer to easily monitor the behavior of the agents with a variety of statistical operations.

Students of social science should be particularly interested in Ascape since it is designed to provide an easy way of abstracting human social interactions into a computational setting. This manual highlights a variety of social science models developed by researchers at the Brookings Institution, including the now well-known Sugarscape models. These examples should be taken as touchstones for developing new model ideas. The best way to learn Ascape is to use Ascape. All of the models discussed in this manual are part of the Ascape download package. New developers are encouraged to look at how these models work and to experiment with, and extend them.

Section 1 of this manual provides a basic introduction to agent-based modeling for those who have no previous experience with it. Even for those with rudimentary exposure to agent-based modeling, Section 1 may still be useful since it sets up many of the examples drawn upon later in the manual.

Section 2 of this manual is a basic introduction to the Ascape modeling framework. This section is required for anyone who has never developed in Ascape before. This section may also be useful for those who have some Ascape experience since it presents a clear exposition of the Ascape architecture. The final part of Section 2 walks the reader through the creation of a rudimentary Ascape model, and so functions as an introduction to the Tutorial in Section 3.

Section 3 develops a basic Coordination Game Model, and then explores various ways in which this model can be experimented with and extended. The tutorial covers various dynamics in agent interaction (imitation, best reply), agent reproduction, experimentation with synchronous/ asynchronous updating, agents with memory, and agents interacting in social networks. There are many other topics that can be explored, and we hope the tutorial will function as a way of getting new developers comfortable enough with the code to start experimenting with Ascape's other functionalities. The API documentation is a useful resource and should be consulted throughout for detailed information on the Ascape classes.

For information about installing and running Ascape, please see the separate Ascape QuickStart Guide. Part I covers the preliminary details of acquiring Ascape. It explains system requirements, and installation. It also explains how to run an Ascape model and how to use Ascape's Control Bar. Part II is a developer-oriented guide that explains the directory hierarchy in the Ascape package, and how to set up a development environment for programming in Ascape. This section also explains what Java and Ascape 'import' files are needed in order to compile Ascape code, and what libraries should be included in the build directory.

Appendix 1 has the complete code samples from the tutorial in Section 3 with the import files and package information in the header. These files are ready-to-compile, and can simply be pasted into properly named files and compiled as Ascape models.

Prerequisites for using this manual:
For Section 1 and the majority of Section 2, the reader should have a basic familiarity with the social sciences as well as working knowledge of one or more modern, object-oriented programming languages. The basic prerequisite is a certain amount of comfort with computing. For the end of Section 2 and for Section 3 the reader should have a basic fluency in Java.

Section 1.
Agent-based Modeling

Introduction

Agent-based modeling is a way of representing systems in terms of interacting agents. It goes under various names across disciplines, including agent-based computational economics (ACE), agent-based social simulation (ABSS, common in Europe), multi-agent systems (MAS) in computer science (mainly artificial intelligence) and individual-based modeling (IBM) in ecology. Agent systems are a generalization of an earlier approach to representing interacting objects (e.g., particles, molecules) known as the cellular automata (CA). A CA, shown below, is a grid, or lattice, in which each square, or cell, is considered to be an agent.

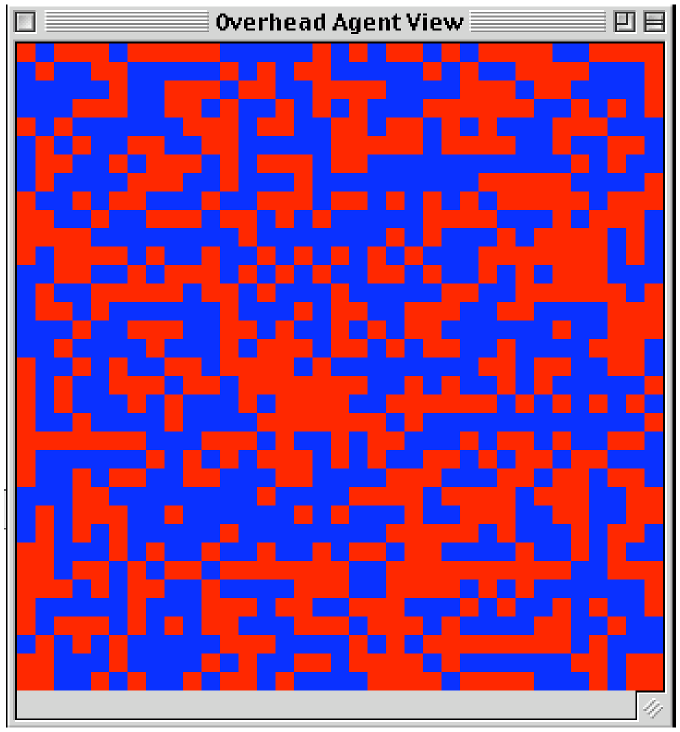


Fig. 1: Schelling Model (at start)

This CA is a version of Thomas Schelling's famous Segregation model. In this model, each agent evaluates its happiness at its current spot and then looks to its immediate neighbors to see whether any of them has a better spot. Each agent is happiest if it has a balanced number of neighbors: 4 blue and 4 red. However, if the neighborhood is unbalanced, each agent prefers to have more neighbors that are like itself than are unlike itself. So, a red agent would prefer to have 5 red and 3 blue neighbors, over having 5 blue and 4 red neighbors, and so on. As the model runs, cells trade properties (i.e., neighbors switch places) until clusters of same-colored neighborhoods form. Ultimately, the model fixates on complete segregation.

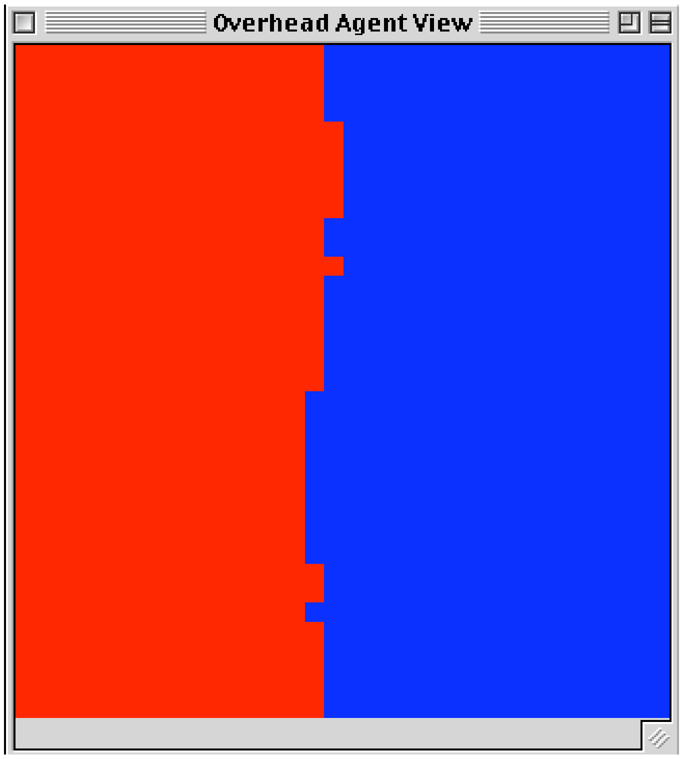


Fig. 2: Schelling Model (at end)

The key to this model is that the individual agents are making their decisions based on local information, yet they collectively produce a coherent global consequence. In this case, the agents collectively produce a consequence that is near the bottom of their preferences in their individual decision-making. Each of the agents in the Segregation model prefers complete heterogeneity above all other options, however the compound effect of each agent's slight preference for sameness in unbalanced neighborhoods pushes the population to complete segregation. The interactions in the above model are entirely local because each agent evaluates its happiness locally, and then trades spots with one of its neighbors. This is called a "spatial" model because an agent's interactions are constrained by the physical structure of its neighborhood. Other versions of this model are designed so that once an agent evaluates its happiness with its neighborhood, it picks random cells on the lattice until it finds one who will trade spots with it. In this case, the model is not entirely localized because agents that are not in the same neighborhood can interact with one another. However, in either case, a central feature of the model, and of CA's generally, is that information (and usually movement) is constrained spatially.

In general, the eight cells that immediately surround any cell constitute its immediate neighborhood. In a fully localized model, this neighborhood, called a Moore neighborhood, determines the set of interactions for any agent in the model. Various permutations on neighborhoods are possible, as some models only use four neighbors (top, bottom, right, and left), and do not count the diagonal neighbors as part of a neighborhood. This is called a Von Neumann neighborhood. Yet, other models extend the neighborhood beyond the first "layer" of cells; thus, for example, a model might include two rows of Moore neighbors in a neighborhood, giving an agent 32 immediate neighbors, or might choose four random, spatially unrelated cells to represent an agent's neighborhood. Thus, although CA models tend to focus on the localized, or spatial, dynamics of agent interactions, neighborhoods are not in principle bound by spatial considerations.

Cellular Automata have been shown to be Turing-complete; so, in principle, anything that can be computed can be computed by a CA. However, part of the strategy of agent-based modeling is to develop models that make complex phenomena more intelligible. A central insight of agent-based modeling is that selecting the right level of abstraction in representing a phenomenon makes all the difference between a good model and a poor model. While it is possible in principle to represent the computationally tractable world as a CA, it is also possible to represent the computationally tractable world as recursive functions, or as a Turing machine. However, neither of these latter two have been particularly productive tools for scientific modeling. While CA's are useful at one level of abstraction, they are not very helpful in showing how agents who are interacting with other agents might also interact with their environment. To provide this functionality, contemporary agent-based modeling tools have added a new layer of abstraction to the traditional CA: Cell Occupants.

In addition to the cell-agent, which is fixed at its location in the lattice, cell occupant agents can move around on top of the cells. Cell occupants can execute the same rules for interacting with one another as the cells in the CA, but they can also interact with the CA cells that are below them. This level of abstraction provides an easy way of modeling how purposive agents, like animals, or decision-theoretic agents, like people, might interact with one another, and also interact with plants or natural resources in the environment (the cells below them).

In the Sugarscape models, agents interact with one another by trading resources, competing for land, forming social ties, etc. Agents must also interact with the landscape by looking for, and harvesting, resources (i.e., sugar plants). A key component of the Sugarscape models is that when agents harvest resources, it is reflected in the landscape. Overharvesting leads to depleted resources, and forces the agents to migrate to a different part of the lattice where resources are unexploited. The Sugarscape models handle the need for all of these levels of interaction by exploiting the cell / cell occupant distinction. The models begin by first populating the cells in the lattice with sugar-plant agents. These cell agents have properties such as size, health, and reproductive potential, all of which can be altered by interaction with human agents. The models then creates a set of cell occupants, or human agents, that walk around the lattice looking for sugar. These agents are assigned the properties of humans: they have metabolism and energy levels, they have harvesting routines, they have trading practices, etc. When a human agent is unsuccessful at finding sugar for too long, it will die; and if it gains excess resources, it will start trade relations with other people.

In the Sugarscape model shown below, the cells are colored on a scale from white to yellow to indicate their sugar levels. Yellow indicates high sugar level, white indicates no sugar. The human agents are initially randomly related to other agents as they search out areas of high sugar concentrations.

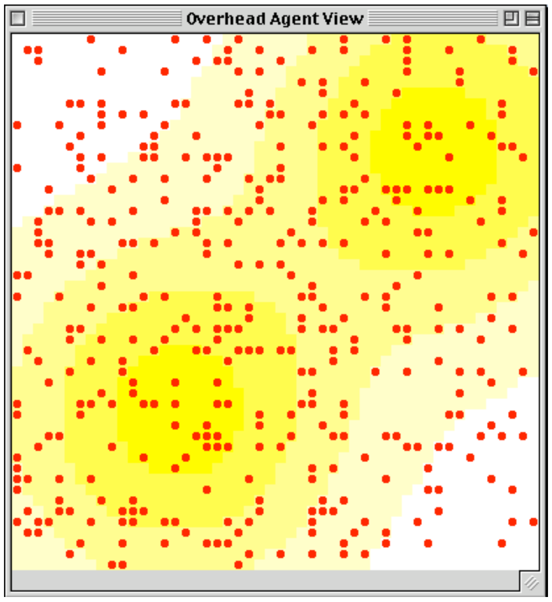


Fig. 3

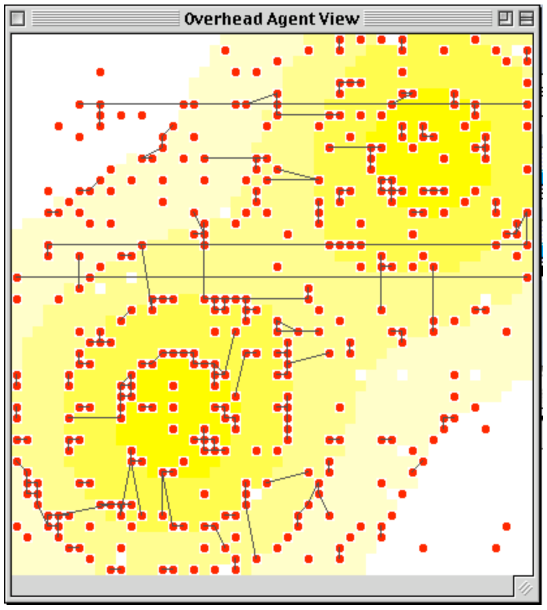


Fig.4

Fig. 3: Sugarscape Model at the start (agents randomly distributed over the lattice).
Fig. 4: Agents with randomly assigned social ties to other agents on the lattice.

Once these human agents find a location with rich resources, they begin to build social ties with one another. These social ties are represented by the lines that identify individual agents as the members of a social group, or clique. As the landscape's resources are depleted, agents are forced to migrate to new sugar-rich areas. Scarcity of resources forces the agents to cluster in sugar-rich areas, and form into tight-nit groups of social relations. In the final stage of the model, shown below, the above population of agents is fragmented into two distinct social groups.

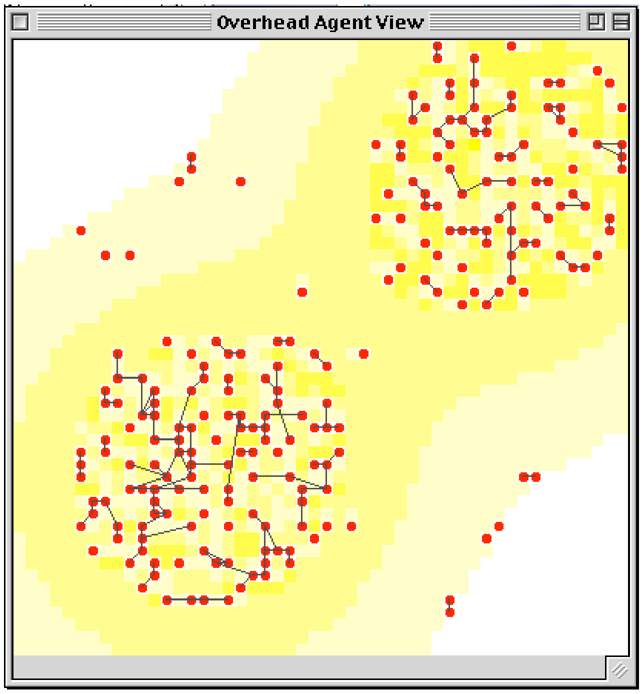


Fig. 5: Sugarscape agents developing localized, close-knit social ties.

The Sugarscape models thus illustrate how the cell / cell-occupant distinction can be exploited to explore how resource abundance and scarcity can influence the dynamics of social network formation. Thus far, we have seen that the basic requirement for an agent-based model is being able to specify a collection of agents and their rules for interacting with one another. We have also seen how this basic requirement has been expanded upon in order to make certain features of the natural world more intelligible, such as the interaction between decision theoretic agents and their environment. Now, let us see how we can use this kind of modeling approach for exploring specific problems in the social sciences.

Social Science Modeling

Game Theory

In the Nash Bargaining game, two agents are asked to divide a "pie". Each agent can select to take 30%, 50%, or 70% of the pie. If the total amount of pie requested by both agents is greater than 100%, then neither of the agents get any pie during that round. Since each agent is trying to get the most pie possible, it would be best for an agent if she could convince others that she would take 70%, so that they will always ask for only 30%. However, this strategy runs the risk that if it is successful, then more people will adopt it, and it will result in no pie for anyone.

As a way of studying the Nash Bargaining Game we can write an agent-based model in which the agents play their neighbors. Each turn the agents play one of their neighbors, keeping a record of the last ten plays. Each agent plays a best response to the record of recent plays, and then updates the record. We can write this model as a CA in which every agent is initially randomly assigned to be either a low-bidder (low = 30%), a fair-player (medium = 50%), or an extortionist (high = 70%).

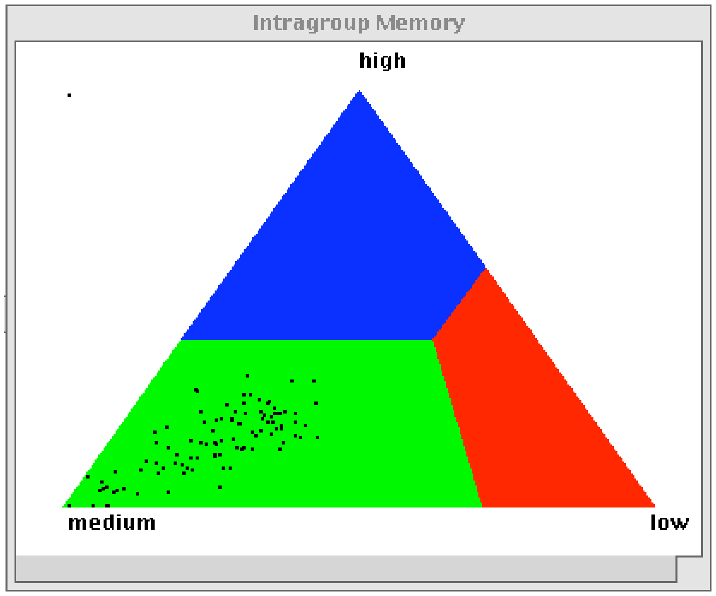


Fig. 6: Simplex view of the Bargaining Model after running a brief time.

If low bidders play extortionists, they will keep playing low-bid. And, if there are low-bidders in the neighborhood, then others will play extortion against them. However, the more that extortion dominates a neighborhood, the more likely it becomes that a neighbor will need to play low-bid in order to get any pie. Of course, this feeds back in the other direction because the more that low bid becomes dominant in a neighborhood, then the more that extortion is the best choice. So, low bid and extortion oscillate in a neighborhood. If a neighborhood becomes fair, then everyone in the neighborhood plays fair, because fairness is the best reply to fairness. Fairness is a self-reinforcing strategy. So, the model will quickly fixates either on all fairness, or on some oscillating pattern of neighborhoods of low-bidders and extortionists. However, to keep the latter from happening, we also introduce the possibility of error. We introduce a small (5%) chance that an agent will not choose to do the best reply response to its record of past plays, but will simply choose a random response. A fair neighborhood is difficult to invade, since fair wins against low-bidders, and extortionists get nothing, so random shocks to a fair neighborhood tend not to disturb it. However, an oscillating neighborhood is very unstable, and if two or more fair players arise, they can quickly reinforce the fairness strategy, and fairness can become dominant in the neighborhood. Over a long period of time, small errors in the model will compound in this way to drive the system toward the mean response: fairness.

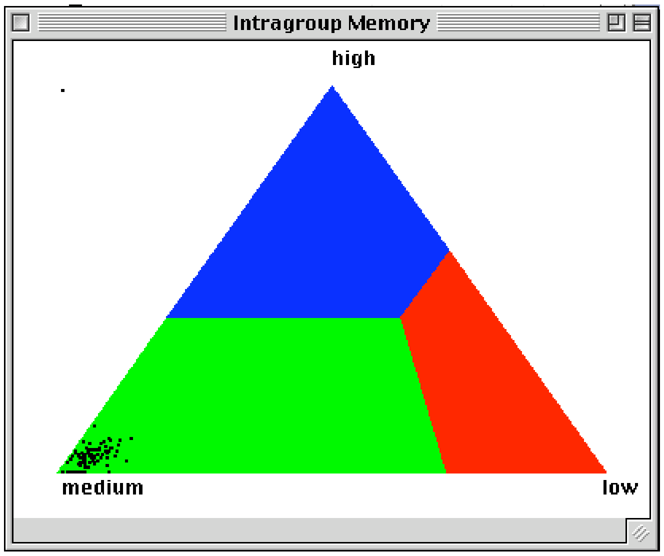


Fig. 7: Simplex view of the Bargaining Model after many iterations

So, this model shows how local interaction, best reply dynamics, and stochasticity (error) combine to drive a bargaining game system toward fairness. This model was developed by Peyton Young.

Evolutionary Game Theory

In the classic Prisoner's Dilemma game, two agents must decide whether to cooperate with, or defect against, one another. Ironically, while both agents are better off if they both cooperate, the payoff matrix is such that the individually highest paying choice is defection. So, both agents wind up defecting and losing out on the benefits of mutual cooperation. There have been a vast number of attempts prove that cooperation is the rational choice in these circumstances. They are all doomed to failure because the game is simply and elegantly structured to produce its paradoxical conclusion. However, a burgeoning literature has taken hold of the problem from an evolutionary perspective. Instead of asking whether an agent would be rational to cooperate in a Prisoner's Dilemma game, this literature asks whether agents that were cooperators could possibly survive in a world where they were forced to interact with agents that were defectors. This field of "evolutionary game theory" removes the decision component from the agents' behavior and asks whether the dynamics of interaction and reproduction could allow "genetically programmed" cooperators to survive better than "genetically programmed" defectors do.

A standard solution to this kind of inquiry is to try to reduce the interactions between dissimilar agents. That is, the goal is to get the cooperators to group together so that they do not interact as much with the defectors. Intuitively, the result of such grouping will be that cooperators will tend to reap the benefits of cooperation, and defectors will be mostly taking advantage of other defectors, and thus the cooperators will do better.

We can easily represent this evolutionary game theoretic scenario in an agent-based model. In the model below, red cell occupant agents (cooperators) and blue cell occupant agents (defectors) play their neighbors in a Prisoner's Dilemma. These red and blue agents are not decision theoretic players, but are pre-programmed to play either cooperate or defect. As the agents increase their wealth through successive plays of the game, they reproduce by hatching clones. The clones are placed on neighboring cells. Thus, as an agent increases in wealth, it creates a neighborhood of same-kind agents with whom to play the Prisoner's Dilemma.

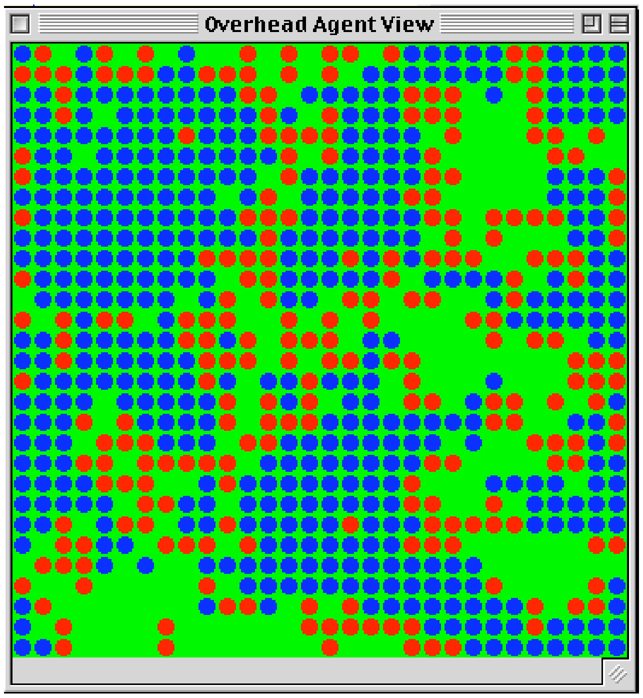


Fig. 8: Demographic Prisoner's Dilemma Model (Blue are Cooperators, Red are Defectors)

As the cooperators reproduce, they create clusters of cooperators, and the same with the defectors. One might expect the defectors to invade the cooperators and take over. However, since the defectors interact mostly with their own progeny, they have a lower average payoff than the cooperators. Thus, by contributing to one another's fitness, the cooperators reproduce more than the defectors. This model is a simple example of how localized interactions in game playing can affect the overall dynamics of a population. It was developed by Josh Epstein.

Organizational Theory

Traditional theories of the firm do not worry about the evolution of firms, but only about the internal organization of existing firms. However, these theories have been ineffective in describing the dynamics of the emergence and elimination of firms from various sectors of the economy. To develop a better understanding of the dynamical processes that surround firm creation and destruction, we can develop an agent-based model of how individual agents (workers) join firms to maximize their payoff from shared productivity and leave firms when their portion of the payoff becomes too low.

To develop an agent-based model of firms, we construct cooperative agents who join firms in order to share in large group payoffs, but as firm size increases workers will lose incentive to keep producing (as their contribution becomes a diminishing fraction of the payoff they receive from the total group effort). So, when firms become too large, the overall productivity of the firm will drop because of the compound effect of non-cooperation by so many workers. Workers will then look to migrate to smaller firms where they will once again get higher payoffs, and be required to contribute cooperatively to secure those payoffs. The dynamics of these individual behaviors produce a Zipf distribution of firm sizes in the economy, and help to explain dynamics of firm emergence and exit from an economy. This model was developed by Rob Axtell.

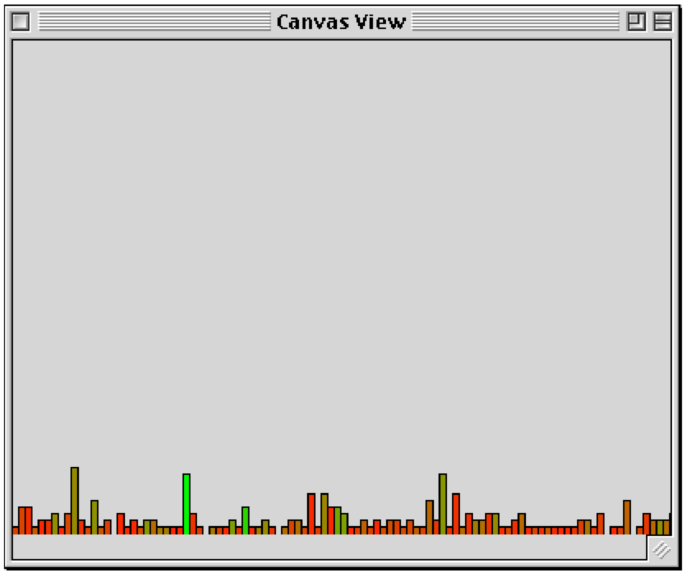


Fig. 8: Firms Model showing the distribution of firm sizes (bar height), and the output of the firms (from red = very productive, to green = non-productive).

Economics / Markets

In recent years, there has been a lot of work bringing agent-based modeling to the analysis of markets, specifically modeling the behavior of traders in the stock market. Simple versions of these models specify rules for traders, such as high-bid, low-bid rules, and rules for selling and buying. These agents often have varying degrees of risk aversion and sophistication in their ability to interpret other agents' actions as indicators for their own behavior. More sophisticated market models have agents whose rules explicitly attempt to predict the behavior of other agents, and whose entire design is built around trying to guess what other agents in the market will do. Yet other models have combinations of 'simple' and 'sophisticated' agents. The goal of all of these models is to replicate the actual behavior of the stock market, and to (ideally) reveal some deep pattern in the rules that the traders use and the correlation of these rule to the path of the market as a whole.

Anthropology

One of the major problems for anthropologists is reconstructing the past from the paltry data available in the present. Agent-based modeling offers anthropologists a new way to explore the path of history: to recreate it. The early American Anasazi nation lived for many years in the Long House Valley of present-day Arizona, and then suddenly disappeared. Anthropologists have tried unsuccessfully to explain how the patterns of horticultural and scientific advancement of the Anasazi, combined with climactic changes, would have led them to migrate elsewhere. Recently, however, anthropologists have teamed up with agent-based modelers to develop a new approach to understanding the migrations of the Anasazi, which has been surprisingly successful.

The agent-based model creates a landscape that matches the historical description of the Long House Valley region during the highpoint of the Anasazi nation. The agents are created to follow simple harvesting and reproduction rules. As resources are exploited, and climactic variables are introduced, the population of Anasazi migrate to follow the available resources. Ultimately, the model shows the path of the Anasazi out of the Long House Valley in a plausible and compelling series of migrations. The model was developed by Rob Axtell and Josh Epstein.

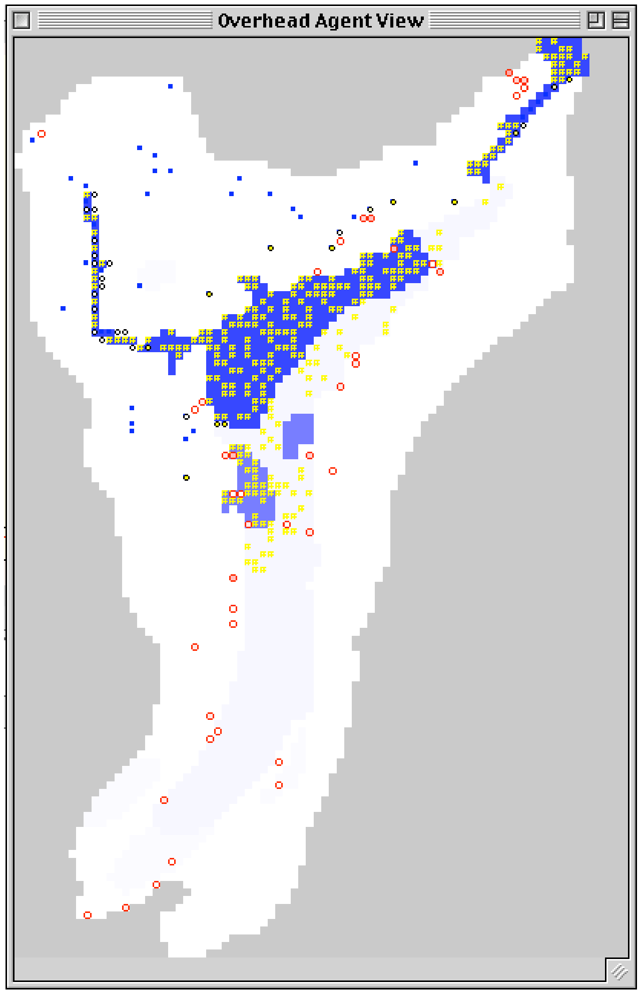


Fig. 10: Long House Valley Anasazi Model

Sociology

The study of social norms is well-known in sociology, but much of this literature explores norms that agents follow self-consciously. As a new direction of inquiry, we might ask whether agents need to be conscious of following a norm in order for it to be effective. In fact, we might hypothesize, it may be just the opposite: social norms may be most effective when we do not think about them at all. To explore this hypothesis, we can develop an agent-based model of how agents follow social norms by sampling their neighbors. In this norms model, agents sample a wide variety of neighbors and 'decide' which norm to follow. As they find that more and more of their neighbors follow the same norm, their sample radius decreases. Sampling is work, and once a norm seems established it is easier to follow it than to keep asking whether it is still the norm. As the sample size is reduced, the likelihood of coming across a different behavior is also reduced, so the norm is reinforced, leading to a further reduction in sample size. Thus, there is a reinforcement between norms and sampling, which leads a norm, once accepted by a significant part of the population, to go to fixation very quickly. When a new norm is introduced, agents need to become 'reflective' again, and take in a wide range of samples. This sequence of thoughtless norm following, followed by a shift in norm behavior and increased sample sizes demonstrates the pattern of punctuated equilibrium common to the evolution of norms. This norm model shows how agents with dynamic sampling radii, and a propensity for 'easy' norm following, will exhibit the basic patterns of norm adoption that have been historically observed. This model was developed by Josh Epstein.

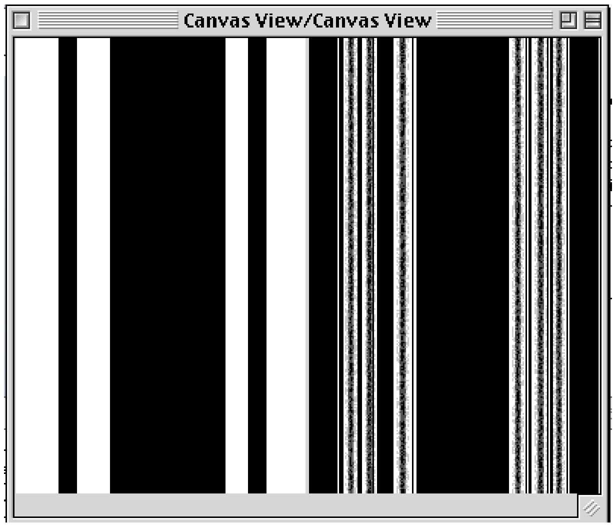


Fig. 11: In the Norms Model, the left panel shows which agents have fixed on a norm of playing either white or black, while the right panel shows how much sampling the corresponding agents are doing. In the deeply entrenched areas (such as the middle 'all black' area) in the left panel, there is almost no sampling (the corresponding side of the right window is black). In the border areas in the left window between white and black, the corresponding areas in the right window are lighter to indicate greater sampling activity. This example shows the model when running under no noise. Adding noise produces migrating patterns of norms.

Political Science

Is a centralized authority better at quelling the uprisings of civil dissidents, or is it better to have a distributed authority? We can develop an agent-based model of civil violence to explore how the presence of authority figures in a society helps to reduce the uprising of civil violence. In this model, we create a large number of citizen agents and a small number of police agents. The citizens are assigned values for their unhappiness and for the 'legitimacy' with which they view the current government. Then the citizens either act out, displaying civil violence, or they conceal their unhappiness because of the threat of being arrested by a police agent. The police agents in the model either follow a centralized patrol routine, or they disperse through the model, randomly exploring the neighborhoods. The model shows that a more disperse police force is much more effective in keeping civil unrest under wraps. It further shows that by experimenting with the values of the citizens' legitimacy and unhappiness, that citizens can tolerate lots of hardship but small, but quick, changes in the legitimacy of a government can lead to widespread civil violence. This model was developed by Josh Epstein.

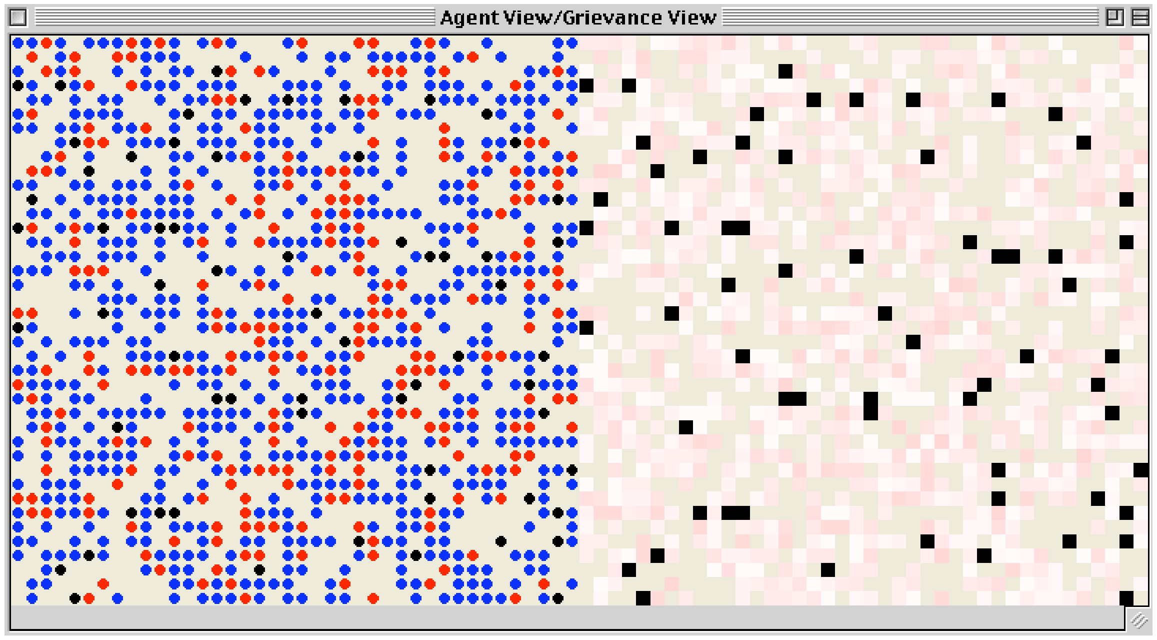


Fig. 12: Civil Violence Model in which red agents are activists, blue agents are quiescent citizens, and black agents are police. The left side of the screen shows the agents' expressed views, and the right hand side shows (on a scale on white equals complete quiescence and light-pink equals complete contempt), the agents' true views.

These examples are just a few of the social science models that we have developed in Ascape. There are many more models in the Ascape suite, and countless more that can be developed, spanning all of the social science disciplines. In the following section, we will learn about the structure of Ascape and begin to build a coordination game model. Following that, in Section 3, we will build an increasingly sophisticated series of Ascape models that should bring even a novice developer up to speed on agent-based modeling in Ascape.

Section 2.
The Ascape Modeling Framework

Introduction

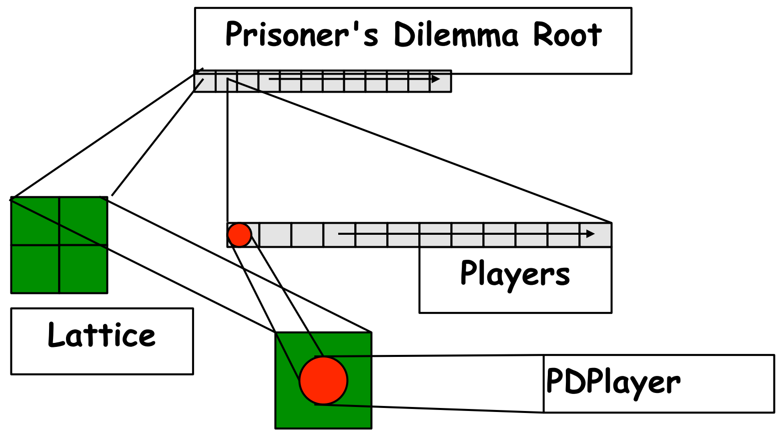
The Ascape agent-based modeling framework has been developed to support the key ideas of agent-based modeling that were presented in Section 1. Ascape is designed to help the modeler make ready use of the concepts of cells, cell occupants and local neighborhoods in order to allow her to quickly start creating agent-based models. In what follows, we will walk through the general structure of an Ascape model, allowing the new Ascape developer to understand the Ascape framework before beginning to build models in the tutorial in Section 3.

The Basic Structure of an Ascape Model

The Agent is the basic structure in Ascape. All of the Ascape objects that we will be concerned with are formally Ascape agents. So far, we have concerned ourselves with cells and cell occupants. Both of these kinds of agents are basic Ascape agents; however cells and cell occupants live inside of collections, and these collections are agents as well. The lattice that the cells comprise is an agent that holds cells. The structure that holds the cell occupants, whether it is called an array, a list, or, more intuitively, a collection, is also an agent.

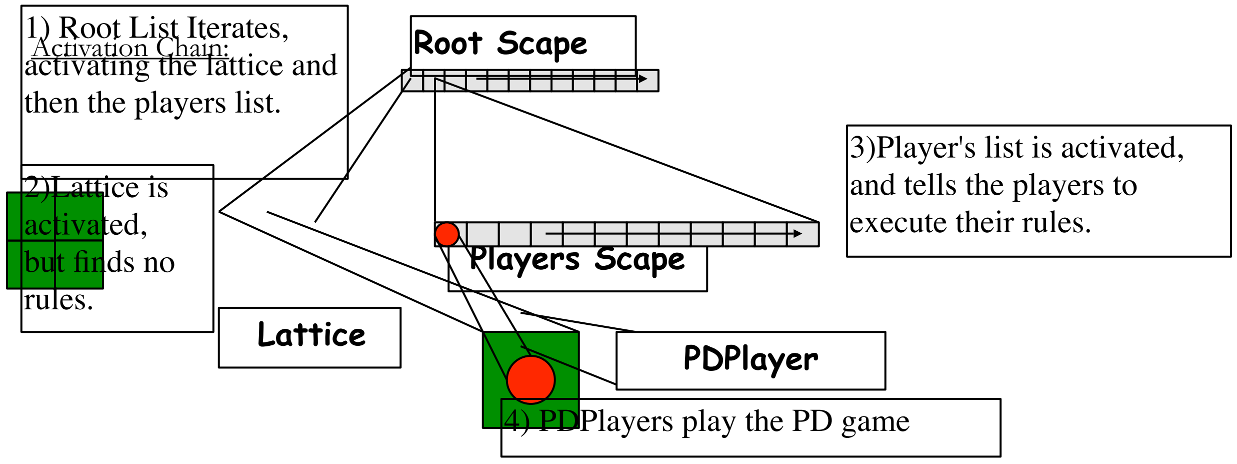
In a fairly basic Ascape model, a collection of cell agents is owned by a lattice agent, and a collection of cell occupant agents is owned by a list agent. In such a model, the lattice and the list sit in the background as containers, and the cells and cell occupants do all of the work. However, this need not be the case, as lists and lattices can interact with each other as agents embedded in still larger structures. As an example of a simple model, consider the prisoner's dilemma model. In this model, the lattice contains a list of cells that are specifically designed for hosting cell occupants. These 'Host Cells' do not do any work, but simply sit inside the lattice agent. The lattice agent itself is also inert in this model. There is also a list agent, called "players", that contains all of the cell occupants agents that are in the model. This list 'holds' the rules for all of its members and when it is activated it tells all of its member agents to execute these rules.

Prisoner's Dilemma Model Structure:



The basic structure of an Ascape model is a container, or list, called the Root. If you imagine a Chinese doll, the model Root is like the largest doll. Each doll that it contains may have still other dolls within it. And, as expected, each layer of the nesting is considered an agent. As you might guess, this means that the model itself is the largest agent. As an agent, the model has one rule: iterate. It executes this rule, and activates its sub-agents. In the Prisoner's Dilemma model, the Root will first activate the Lattice (because, it just so happens it was added first, and so it is in the first position), and then it will activate the players list. When the lattice is activated, it looks to see if it has any rules for its agents. If so, then it tells each agent to execute. In this case, it does not, so it does nothing. When the player's list agent is activated, it looks to see if it has any rules for its agents, and then, in turn, it activates them and they each execute the set of rules.

Activation Chain:


1) Root List Iterates, activating the lattice and then the players list.
Root Scape
3)Player's list is activated, and tells the players to execute their rules.
2)Lattice is activated, but finds no rules.
Players Scape
Lattice
PDPlayer
4) PDPlayers play the PD game

Ascape's term of art for a collection of agents is a 'scape'. Intuitively, this means that the basic structure of an Ascape model is nested scapes. In the Prisoner's Dilemma model, the *Lattice* scape is a collection of cell agents, and the *Players* scape is a collection of cell occupant agents. The model itself, *Prisoner'sDilemma*, is a Root scape that contains two elements (or agents).

Constructing the Agent Scapes

For any scape that a developer will create, there are three basic properties that should be assigned to it.

1) The kind of agents that it contains,
2) The execution order of those agents, and
3) (optionally) The statistical operations being performed on the agents

Specifying Agents in the Model

In Ascape, agents are created by writing a Java class that describes their properties and behavioral rules. When a developer is writing a new class for an agent, she begins by creating a subclass of an existing agent class. The reason for writing a subclass is that all of the properties of the parent class, or superclass, are inherited by the subclass. In general, the base class for any agent is the Cell class. Host Cells, Cell Occupants, Scapes, and Lattices are all subclasses of the Cell agent.

It will seem strange at first that the Cell agent is more primitive than the Scape agents, because, for example, a Scape agent is a container for Cell agents. However, the key to using Ascape is to appreciate that Scapes can behave like Cells. The formal class hierarchy is as follows:

```
-Agent
        -Cell
                -Host Cell
                -Cell Occupant
                        -Scape
```

This hierarchy structure also means that a Scape, since it is a subclass of Cell Occupant, can reside on a Cell. And, since the Scape is a subclass of Cell, each of the member agents for a Scape Graph could be themselves be Scapes. This hierarchy in which Scapes are subclasses of Cells and Cell Occupants is the formal implementation of the idea that scapes are 'fully-fledged' agents that can interact with one another, and with their parent scapes, just like Cell and Cell Occupant agents. Once a developer understands that the rules that iterate through a scape can apply to any kind of agent that belongs to that scape, she understands how to develop models in Ascape. For a more complete view of Ascape's class hierarchy, consult the API documentation included in the download.

Specifying the Execution Order

All scapes (both the scape graph and all of the scape lists) have a function that allows the developer to set the execution order for the agents in the scape. The execution order determines whether the behaviors of the agents in the model are performed synchronously or asynchronously. So, for example, let us say that all of the pdplayer agents have the following set of rules:

1. pick a random neighbor
2. play the pd with that neighbor
3. move to a new spot.

If the scape list *Players* executes in RULE_ORDER, then the agents will perform their behaviors synchronously. Each agent will pick a random neighbor. Once every agent has picked a random neighbor, then every agent will play the PD with that neighbor. Once every agent has done this, then every agent will move to a new spot. So, in this case, all agents perform their rules in synchronization (synchronously). Everyone is picking, playing, and moving at the same time. If the scape list *Players* executes in AGENT_ORDER, then the first agent in the *Players* list will pick a random neighbor, play that neighbor, and move to a new spot. Then the next agent in the *Players* list will also perform this set of rules. This continues until all agents have performed the full set of rules, and then *Players* starts a new iteration with the first agent again. In this case, the agents perform their rules asynchronously, since an agent (B) selected later in the iteration through the *Players* list may actually choose to play an agent (A) that had been selected earlier in the iteration, and has recently moved into B's neighborhood.

Specifying the execution order simply involves using the setExecutionOrder() function for each scape.

Specifying the Statistical Operations

Statistical operations are an important way of getting information about the contents of a scape. There are a range of operations available, and the developer can always extend existing operations to create new ones. In a simple example from the PD model, we may want to chart the number of cooperators against the number of defectors. A simple statistical operation would be to count the number of agents in the '*Players*' scape that are red, and to name this statistic the 'number of defectors'. Similarly, we can count the number of agents in '*Players*' that are blue, and plot this statistic as the number of cooperators.

A more sophisticated statistical operation, also from the PD model, would be to record the wealth of each agent that satisfies a basic condition (such as being red or blue), and then to average the sum of these values. So, for the '*Players*' scape, we would make a statistical operation that records the wealth of every red agent, and then divides through by the number of red agents. Similarly, we could do the same with the blue agents. We can then graph these values, and see the average payoff for cooperating versus the average payoff for defecting.

Additional Scape Properties

In addition to the three basic properties of every scape, there are also properties that are particular to different kinds of scape graph. In this case, we are working with a 2-dimensional lattice. First of all, since the scape graph determines the geometry of the neighborhoods in the model, this needs to be set explicitly by the developer upon the creation of the lattice.

As explained in Section 1, there are two basic kinds of neighborhoods in a 2-dimensional lattice: Von Neumann and Moore. The Moore neighborhood includes the eight cells immediately surrounding a cell, and the Von Neumann neighborhood includes the four cells that border along the top, bottom, right, and left of a cell.

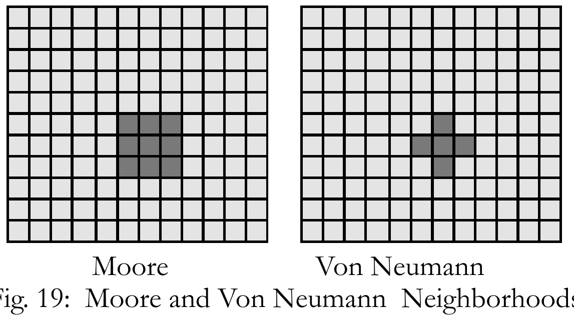


Fig. 19: Moore and Von Neumann Neighborhoods

As mentioned earlier, different kinds of neighborhood geometries might be used, and some models forego the spatial geometry altogether and rely upon a network graph as the basic structure of the lattice. These latter kinds of models, so-called 'networks models', will be introduced in the tutorial in Section 3.

A final property of the scape graph that needs to be set by the developer is the actual dimensions of the scape graph. Usually the developer creates two variables, 'lattice_height' and 'lattice_width', and uses these to create the dimensions of the lattice.

A First Introduction to Ascape Code

Before starting the tutorial in Section 3, it will be helpful to get an overview of how the Ascape code base is structured. Ascape is essentially a set of Java libraries that easily allow the developer to make collections of agents (i.e.,. scapes) and to specify rules for the agents' interactions with one another. There are about 150 Java files, totaling about half a million lines of code, in every Ascape model. Happily, in order to create an Ascape model, a developer only needs two write a minimum of two Java files, totaling about 50 lines of code.

The two basic files that every model requires are:

1) A class that defines the model itself
2) A class specifying some type of agent and its behavioral rules.

In what follows, we will create the basic framework for an Ascape model. This will involve creating the first required file, the model class, and it will illustrate how to implement the basic structural features discussed above. In the tutorial in Section 3, we will develop this framework into a fully functioning model, and show how to expand on it.

The Basic Framework for a Coordination Game Model

A good example model, similar to the Prisoner's Dilemma model from Section 1, is a model of a basic coordination game. In the Coordination Game model, agents try to coordinate on a simple activity. Let us say that agents want to coordinate their choice of colors. The payoff matrix, shown below, indicates that agents are paid equally well for coordinating on red or blue. Their payoff is poor, however, if they fail to coordinate with the other player.

	Red	Blue
Red	1, 1	0, 0
Blue	0, 0	1, 1

Coordination Game Payoff Matrix.

The agents in the coordination game model will be cell occupant agents that walk around the lattice and play one another. Among their properties, these agents will have access to the above payoff matrix, they will have a memory of their five most recent plays, and they will have a set of rules telling them how to play and move around the lattice.

To create the basic framework for the model, we need to create the first of the two required files mentioned above: the class that defines the model. Let us call this class "CoordinationGame.java".

In standard Java, the CoordinationGame class is defined with the following line of code:

```
public class CoordinationGame extends Scape {

}
```

The CoordinationGame class uses the Java keyword extends t o make it a subclass of the Scape class. As discussed above, a scape list is a container that holds different kinds of agents. Because the class CoordinationGame is a subclass of Scape, it will inherit all the basic properties of a List. To construct the Coordination Game model we simply need to add a scape graph and some agents to the

CoordinationGame class. Thus, CoordinationGame class is the Root Scape for the model, and will contain a scape graph containing cell agents and a scape list containing cell occupant agents.

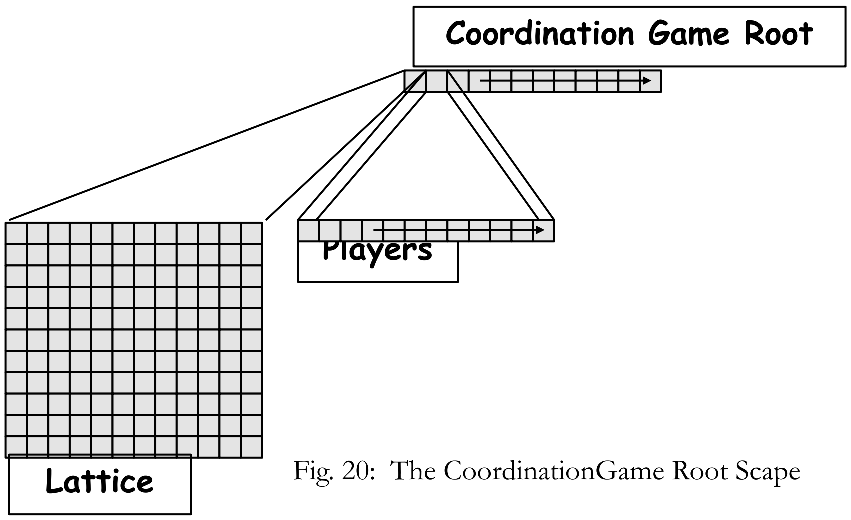


Fig. 20: The CoordinationGame Root Scape

The first thing we do in the class is to create some variables. First, we create some integer variables to hold some information about the model. We create a variable for the lattice height, one for lattice width, and one to assign the number of cell occupant agents that we will create.

```
public class CoordinationGame extends Scape {

        public int latticeHeight = 30;
        public int latticeWidth = 30;
        public int nPlayers = 200;

}
```

We have assigned the values 30 x 30 to the variables that will be used to create the dimensions of the scape graph. These values can be changed later if we so desire. We will initially create 200 agents to play the coordination game.

Next we create some instance variables for classes that we will need to instantiate in order to create the scape graph of host cells, and the scape list of players. One of these variables ('lattice') will serve as the instance of our scape graph, and one ('players') will serve as the instance of our scape list.

```
public class CoordinationGame extends Scape {

        public int nPlayers = 200;
        public int latticeWidth = 30;
        public int latticeHeight = 30;
        Scape lattice;
        Scape players;

}
```

With those five variables in place, the next order of business is to make the constructor method. Typically Java classes are made using a constructor method that initializes all of its variables. However, all of the constructor methods for the basic Ascape classes have been written, so the standard way to create a subclass in Ascape is just to reference the constructor method of the new class's superclass.

So, to construct the CoordinationGame class, we write the following createScape method:

```
        public void createScape() {
                    super.createScape();
        }
```

This createScape method calls the createScape method in CoordinationGame's superclass (Scape). The constructor in Scape creates all of the necessary functionality to make the CoordinationGame class function as a fully fledged scape list. The model, thus far, looks as follows:

```
public class CoordinationGame extends Scape {

      public int nPlayers = 200;
      public int latticeWidth = 30;
      public int latticeHeight = 30;
      Scape lattice;
      Scape players;

      public void createScape() {
            super.createScape();

      }
}
```

After we call the Scape constructor, we need to construct our scape graph, our 'players' scape list, and our individual agents. The first thing we will make is the scape graph. We will create a new scape graph with a Von Neumann geometry, and assign it to the 'lattice' variable.

```
lattice = new Scape(new Array2DVonNeumann())();
```

'ScapeArray2DvonNeumann' is a readymade scape graph geometry. We can assign it to our lattice by simply instantiating the predefined Ascape class ScapeArray2DVonNeumann. This class, somewhat intuitively, will create a two dimensional lattice in which the agents use Von Neumann neighborhoods in their local interactions.

Next, we assign the prototype agents to the lattice.

```
lattice.setPrototypeAgent(new HostCell());
```

Since the Coordination Game model does not require the cell agents to have any behavior, we can simply populate the lattice with host cell agents. Host cell agents allow cell occupants to walk around on top of the lattice.

Since the cell agents in the lattice will not have any behavioral rules in this model, we will not specify an execution order for the scape graph. However, we still need to specify the dimensions of the lattice.

```
lattice.setExtent(latticeWidth, latticeHeight);
```

This call creates the lattice with the specified dimensions, in this case 30 x 30.

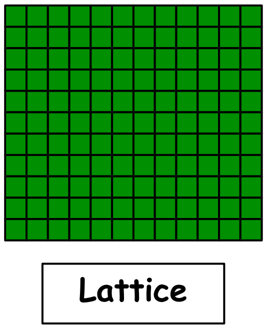


Fig. 21: The Scape Graph

Thus far, the model looks as follows:

```
public class CoordinationGame extends Scape {

public int nPlayers = 200;
      public int latticeWidth = 30;
      public int latticeHeight = 30;
      Scape lattice;
      Scape players;
      Overhead2DView overheadView;

      public void createScape() {
            super.createScape();

            lattice = new Scape(new Array2DVonNeumann());
      lattice.setPrototypeAgent(new HostCell());
            lattice.setExtent(new Coordinate2DDiscrete(latticeWidth,
      latticeHeight));

      }
}
```

Next, we are going to create the scape list and assign agents to it. And finally, we will add both the scape list and the scape graph to the Root Scape.

First, we need to create an instance of the class CoordinationGamePlayer. Above, we mentioned that a developer must author a minimum of two files to make an Ascape model: the first file, the model class, is what we are constructing. The second file, the agent class, is (in this case) the CoordinationGamePlayer class. This class defines the agents who are playing the Coordination Game. Since the agents in the model are cell occupants, the CoordinationGamePlayer class will be a subclass of the CellOccupant class, and so will have all the basic properties of cell occupant agents.

We have not made this class yet (we go through this in the tutorial in Section 3), but let us say, for exposition's sake, that it has already been written. So, assuming that the CoordinationGamePlayer class exists, we need to do the following. We need to create an instance of the class, set the host scape for these agents, and then make these agents the prototypical agent for the 'players' scape list. All cell occupant agents, i.e., subclasses of the CellOccupant class, have the function setHostScape().   This function is required in order to tell the newly created cell occupants where they live; i.e., we must explicitly assign our instance of the CoordinationGamePlayer agents to this model's scape graph. This assignment of players to a lattice is how the individual agents that we will add to the 'players' scape will know what kind of world (i.e., what geometry, what kind of cell agents, etc.) they are located in.

```
CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
      cgplayer.setHostScape(lattice);
players = new Scape();
players.setPrototypeAgent(cgplayer);
players.setExecutionOrder(Scape.RULE_ORDER);
```

In the code snippet above, we first create an instance of the CoordinationGamePlayer class (called 'cgplayer') and then we set the host scape for these agents to be the scape graph 'lattice' that has already been created. Now, the agents in the model have been assigned to live on this model's scape graph. Then we create the 'players' scape using the 'players' variable that we created at the beginning of the model. We assign the cgplayer agent as the prototypical agent for the 'players' scape. So, the cgplayer agents are all collected into the 'players' scape, and their execution order and statistical operations will be determined by the settings on this scape. In this section of the manual, we are not going to demonstrate statistical operations (this will be covered in the tutorial in Section 3). So, the final operation is to set the execution order for the 'players' scape.

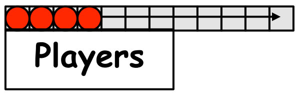


Fig. 22: The Players Scape populated with Coordination Game Player agents

Finally, we add the 'lattice' scape graph and the 'players' scape list to the Root Scape

```
add(lattice);
add(players);
```

Now the basic framework of the model has been constructed.

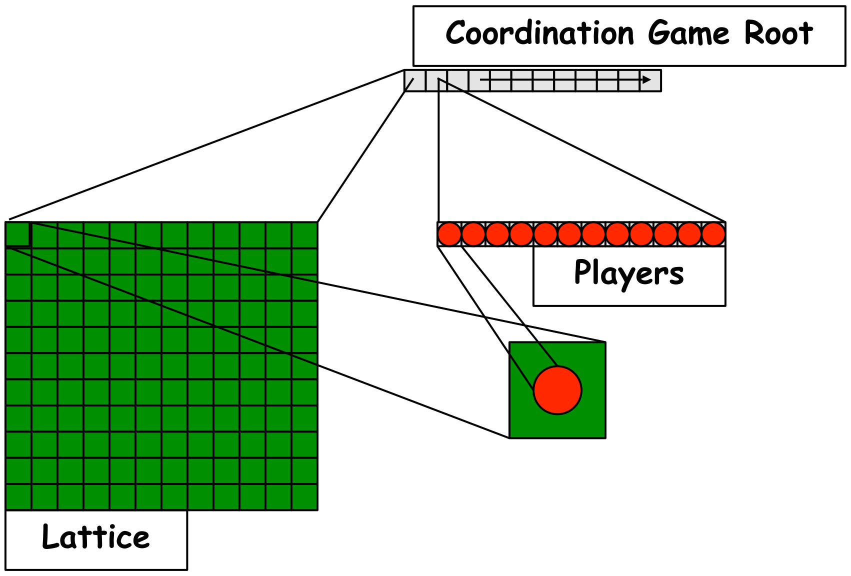


Fig.23: Basic Structure of the Coordination Game

In total, the model thus far looks as follows:

```
public class CoordinationGame extends Scape {

public int nPlayers = 200;
public int latticeWidth = 30;
public int latticeHeight = 30;
Scape lattice;
Scape players;
Overhead2DView overheadView;

public void createScape() {
       super.createScape();
       lattice = new Scape(new Array2DVonNeumann());
       lattice.setPrototypeAgent(new HostCell());
       lattice.setExtent(latticeWidth, latticeHeight);

       CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
      cgplayer.setHostScape(lattice);
       players = new Scape();
       players.setPrototypeAgent(cgplayer);
      players.setExecutionOrder(Scape.RULE_ORDER);

       add(lattice);
       add(players);

       }
}
```

The above code snippet is the basic framework for an Ascape model. There are many details that have been omitted so that we could highlight the essential features of the model. In the following section, we will walk through the construction of some more elaborate examples, creating working Ascape models and showing how to expand on them.

Section 3.
The Ascape Tutorial

Introduction

In the last part of Section 2, we built the basic framework for a Coordination Game model. In what follows, we will flesh out that framework to make a working model, and then we will expand on that model to illustrate some of Ascape's more interesting functionalities.

The Coordination Game Model

The model we have created so far is below. The Java operator for commenting code (//), will be used throughout the code samples to add annotations.

```
public class CoordinationGame extends Scape {

//These three integer variables define the dimensions of the
//lattice and the number of agents in the model
public int nPlayers = 200;
public int latticeWidth = 30;
public int latticeHeight = 30;

//These two instance variables will be this model's scape graph
//and it's players scape.
Scape lattice;
Scape players;

//The 'createScape' method constructs the scapes for the model, specifies
the //agents and execution order, and adds the scapes to the model.
public void createScape() {

        //first we call the constructor for the Scape class
        super.createScape();

        //next we create the 2Dlattice with a von Neumann neighborhood //
        structure, set its prototypical agents, and set its dimensions
        lattice = new Scape(new Array2DVonNeumann());
```

```
            lattice.setPrototypeAgent(new HostCell());
            lattice.setExtent(latticeWidth, latticeHeight);


            //then we create an instance of the CoordinationGamePlayer class
            so //that we can assign it to the lattice and make it
            //the prototype agent for the players scape.
            CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
           cgplayer.setHostScape(lattice);

            //then we create the players scape, set the prototype agent, and
            set //the execution order.
            players = new Scape();
            players.setPrototypeAgent(cgplayer);
           players.setExecutionOrder(Scape.RULE_ORDER);

            //finally, we add the specified scape graph and the
            //specified players scape to the model.
            add(lattice);
            add(players);

            }
    }
```

In order to build a working Ascape model, we need to expand this basic framework to include some key functionalities that have not been discussed. Section 2 outlined the basic conceptual structure of a model. This part of section 3 covers some technical aspects to constructing an Ascape model that have less to do with conceptual architecture and more to do with details of implementation.

Finishing the CoordinationGame Class

The View Object.

When we create a scape graph, it takes on all the properties of a CA, but it is not yet a 'graphical' component of the model. The scape graph is a mathematical object: it is an N x N lattice populated with cell agents. Once we add the lattice to the model, the Java engine stores all of its information but the engine does not know how to draw the lattice so that we can watch it run. Thus, if we were to run the above model, it would calculate the outcome, but we would not be able to see it. In order to make the model visible, we need to create a view object and add it to the scape graph. Statistical operations, which we will handle below, are managed similarily; in order to collect statistics on a model, we need to create a statistics view and add it the appropriate scape.

There are numerous view objects that come standard with Ascape. Of course, you can always extend one of these classes to write your own. The standard view most often used to show the scape graph is the basic, 2D overhead view. This view simply represents the scape graph as a 2D lattice with the (0, 0) coordinate (origin) in the top, left corner. This view object is called the Overhead2DView.

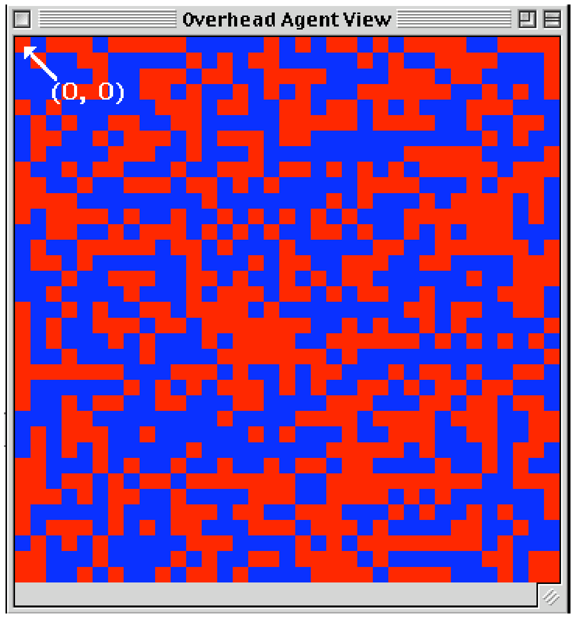


Fig. 24: Overhead2Dview

There is also an overhead 2D view that allows the developer to relativize the origin of the lattice to any coordinate on the graph. This is called OverheadRelative2DView.

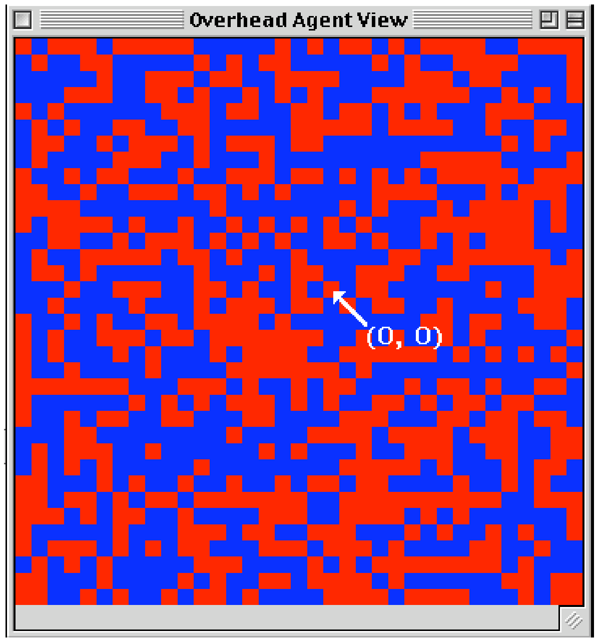


Fig. 25: OverheadRelative2DView

In some Ascape models, agents do not interact on a spatial graph. For example, in the Firms model, every agent is located in a 1D list that is divided up into smaller collections, called firms. There is no spatial component to this model, since all interactions occur between agents simply based on their membership in a 1D list, and not on their location in it. In this model, there are no neighborhoods, but only amorphous collections of agents. In the Retirement model, agents are located on a 2D scape graph, but their significant interactions happen through network relations. In both of these models, simply showing an overhead 2D view would be meaningless. So, they employ views that show the relevant 1D data. In the Retirement model, the entire players list is shown horizontally, and the agents are colored by their properties (retired or not). This horizontal array scrolls to show the new state of the players list at each time step. This is called a Scrolling1DView.

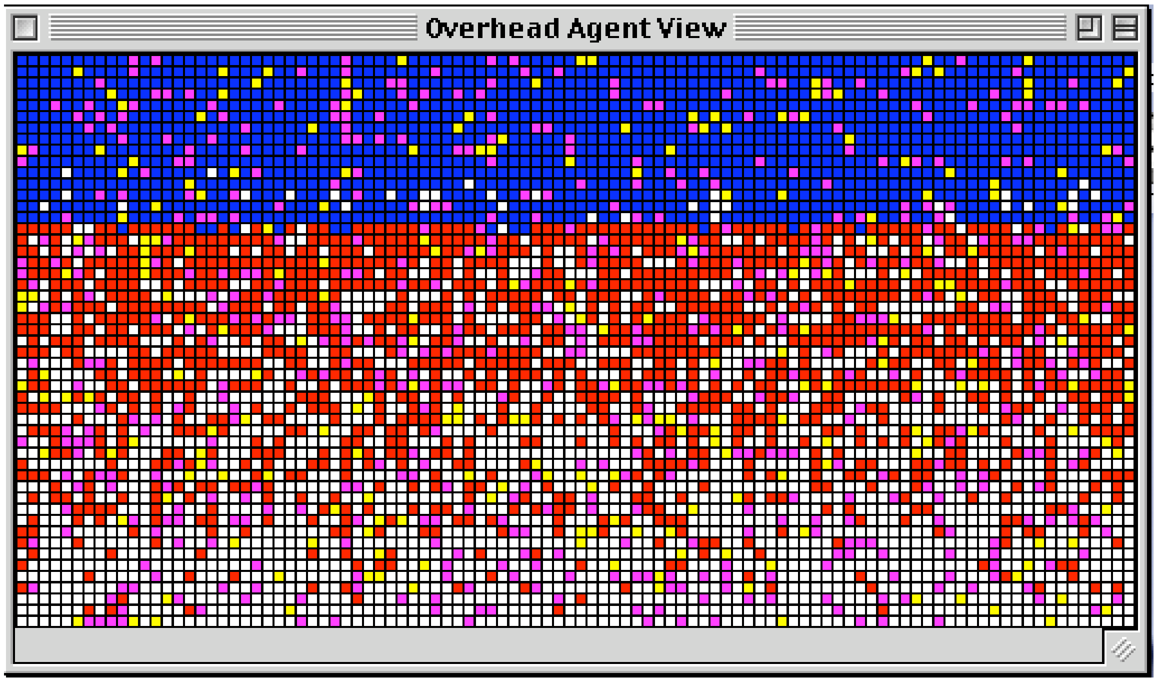


Fig.26: Scrolling1Dview (Retirement model)

The Firms model does not use a lattice at all. In the Firms model, agents switch firms by moving from sub-list to sub-list (or “firm to firm”) within the main players list. The view object for this model simply displays a vertical list of the firms (sub-lists), showing the number of agents in each firm list. This view object, called the FixedStretchyView, allows the developer to easily visualize comparisons in the sizes of sub-lists.

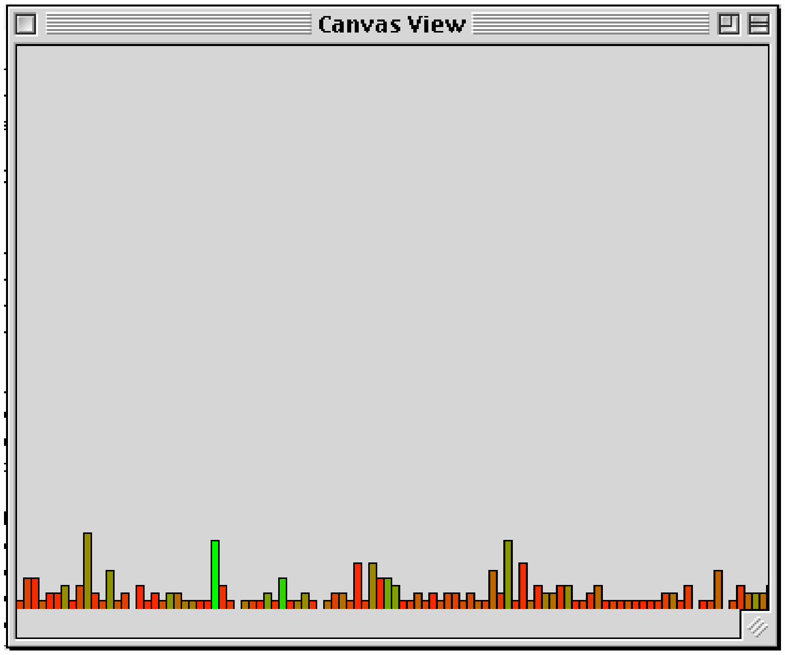


Fig.27: Fixed Stretchy View

The Coordination Game Model is a fairly basic spatial game on a 2D lattice, so we will use the basic Overhead2DView class. The first thing to do is to add a variable to the CoordinationGame Class that can hold the new view object. This variable will be of type Overhead2DView because it will hold an instance of the Overhead2DView class.

```
public class CoordinationGame extends Scape {

        public int nPlayers = 200;
        public int latticeWidth = 30;
        public int latticeHeight = 30;
        Scape lattice;
        Scape players;
        //This is the view object variable that will hold our instance of
the //Overhead2DView class
        Overhead2DView view;
        .
        .
        .
}
```

The vertical ellipses in the code examples:
.
.
.
will be used to avoid redundancy of code that is inessential to the example.

Next, we will create a method called createGraphicViews(), in which we construct the view and add it to the scape graph. We do not need explicitly to call the createGraphicViews() method. Like createScape(), createGraphicViews() is automatically called on startup.

```
public void createGraphicViews() {
       //call the basic view setup for a Scape List
       super.createGraphicViews();
       //Create the new view
       view = new Overhead2DView();
      //Set its cell size to, say, 15
       overheadView.setCellSize(15);
       //add the view to the scape graph.
       lattice.addView(overheadView);
}
```

In the createGraphicViews() method, we first call the Scape class's createGraphicViews() method. This insures that any general setup routines defined in the superclass will be performed. We then create the new Overhead2Dview with the 'view' variable, and then we set the cell size. Setting the cell size does not affect the dynamics of the model at all, but simply determines how much of the screen the model will occupy. Finally, we add the new view object to the scape graph. View objects should be thought of as windows into a scape. They attach to the scapes to present representations of their agent population. Some view objects attach to scape graphs, other view objects (such as charts) can attach to other kinds of scapes. But, in general, the purpose of a view object is to visualize the contents of a scape. Once we add the 'overheadView' object to the lattice, we have created a window into the scape graph.

Creating All of the Agents

In setting up the model, we must tell the players scape how many of the cgplayer agents we want to have. We have already created an integer variable 'nPlayers', to which we assigned the value '200'. Now, we need to used that value to tell the players scape how many agents to add to itself. We do this with the onSetup() method. Like CreateScape() and Creategraphicviews(), public void scapeSetup(ScapeEvent scapeEvent) is called automatically when the model launches.

```
public void scapeSetup(ScapeEvent scapeEvent) {
 ((Scape) agents).setExtent(new Coordinate1DDiscrete(nAgents));
}
```

The onSetup() method tells the 'players' scape to set its size to fit an array of nAgents, which, in this case, is 200. Since cgplayer was assigned as the prototypical agent for the 'players' scape, this scape now has 200 agents of type cgplayer.

The basic structure of the working model is now complete. It looks as follows:

```
public class CoordinationGame extends Scape {

       //create variables
       public int nPlayers = 200;
       public int latticeWidth = 30;
       public int latticeHeight = 30;
       Scape lattice;
       Scape players;
       Overhead2DView overheadView;

       //create scapes and create agents
       public void createScape() {
              super.createScape();
              lattice = new Scape(new Array2DVonNeumann());
              lattice.setPrototypeAgent(new HostCell());
```

```
                lattice.setExtent(new Coordinate2DDiscrete(latticeWidth,
                latticeHeight));

                CoordinationGamePlayer cgplayer = new
                CoordinationGamePlayer();
               cgplayer.setHostScape(lattice);
                players = new Scape();
                players.setPrototypeAgent(cgplayer);
               players.setExecutionOrder(Scape.RULE_ORDER);

                add(lattice);
                add(players);

        }

        //create views
        public void createGraphicViews() {
                super.createGraphicViews();
                view = new Overhead2DView();
                overheadView.setCellSize(15);
                lattice.addView(overheadView);
        }

        //populate the model with agents
        public void onSetup() {
                 ((Scape) agents).setExtent(new Coordinate1DDiscrete
        (nAgents));
        }

}
```

So, with these four steps we have
1) created our variables
2) created the scapes and the agents
3) created the views
4) populated the model with agents

This model is ready to run except for the small problem that the class CoordinationGamePlayer does not exist. Once we create this class, we will be able to fill the 'players' scape with cgplayer agents, and run the model.

Making the Coordination Game Player Class

The coordination game agent is very basic. It simply looks around in its local neighborhood (which has been defined by the lattice as a von Neumann neighborhood), and picks a random neighbor to play. The payoff matrix looks as follows.

	Red	Blue
Red	1, 1	0, 0
Blue	0, 0	1, 1

Fig. 28: Coordination Game Payoff Matrix

In this coordination game, the agents are trying to coordinate on color. Each round, agents either get a 0 for failing to coordinate, or a 1 for coordinating. Next, we need to choose a mechanism for how the players will decide what color to play. They could play a best reply, or they could play imitation, or they could play some more complicated version of a rational choice strategy. To start, we will make the agents very dumb and have them be simple imitation agents. These agents look around the neighborhood for the agent who has scored the highest on its five most recent plays, and they imitate the color of that agent.

So, the properties of the cgplayer agent are as follows. It has:

1) a variable for its color
2) an array that holds its scores on its last five plays
3) a variable to hold the sum of its last five scores
4) rules for picking a random neighbor and playing against it
5) a rule for imitating the most successful neighbor.

So, the agents only need to have:

1)3 variables (color, recent total score, array of recent plays)
2)2 rules (imitate best in neighborhood, pick a random neighbor and play)

To create the CoordinationGamePlayer class, first we setup the variables and initialize the class.

```
public class CoordinationGamePlayer extends Cell Occupant{

        //create our variables
        protected Color myColor;
        protected int totalScore;
        protected int[] recentPlays;

        //we also add a variable so we can keep track of the first five
        plays.
        protected int count = 0;

        public void initialize() {
              if (randomInRange (0,1) > 0)
             {
                   myColor = Color.red;
             }
             else
             {
                   myColor = Color.blue;
             }
              recentPlays = new int [5];
        }

}
```

As discussed in Section 2, the CoordinationGamePlayer agent is a cell occupant agent, so it must extend the class CellOccupant. The initialize() method is called automatically when each new agent is created. This method assigns either red or blue to the agent, with a probability of .5. It also creates the 'recentPlays' array with a length of 5.

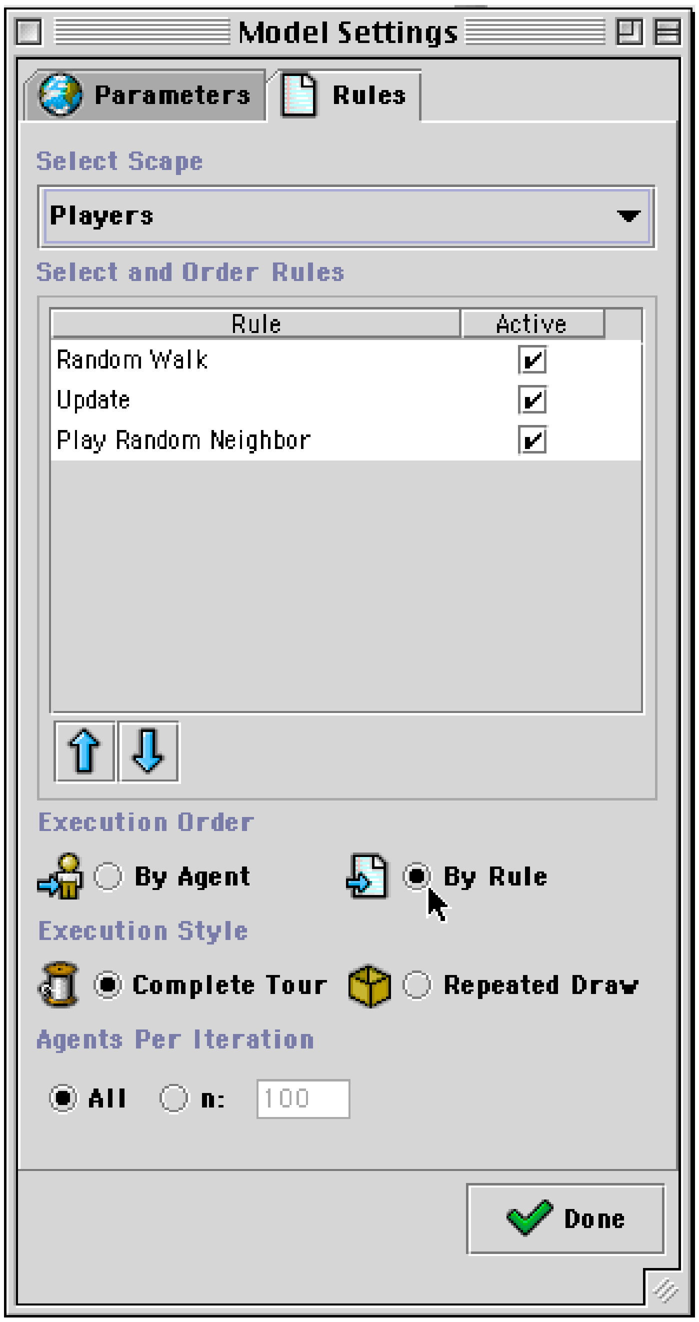
In order for the variable 'myColor' to effect the color of the agent when it is rendered on the screen, we must have a method getColor() that can be called by the system. This method is also useful so that other agents can find out what color an agent is.

```
Public Color getColor(){
      Return myColor;
}
```

Now that we have created and initialized our variables, we need to make some rules for the agents.

Rules in Ascape.

In Ascape, rules are not attached to individual agents but to the scapes in which they are located. Intuitively, every agent in the 'players' scape will have the same set of rules (e.g., imitate the most successful player in the neighborhood, find a partner and play, etc.). This list of rules executes across all active players in the scape. In addition to efficiency, a benefit of having the scape own the rules for the agents is that it gives the user the ability to change the rules at runtime. Scape-level properties can be edited in the Settings window while the model is running. This allows the user to change the order of the rules, to make the rules execute in AGENT-ORDER, or RULE-ORDER (i.e., asynchronously or synchronously), and to eliminate some rules from the agent's behavior, all without having to change the code.



Model Settings

Parameters | Rules

Select Scape

Players

Select and Order Rules

Rule	Active
Random Walk	✓
Update	✓
Play Random Neighbor	✓

Execution Order

By Agent [✓ By Rule]

Execution Style

[✓ Complete Tour] Repeated Draw

Agents Per Iteration

[✓ All] n: 100

Done

Fig.29: Settings window (Rules Tab) in Running Model

This is a basic concept in Ascape programming: designing scape-level properties modularly, so that we can experiment on the population of agents without having to rewrite the agent code each time.

For convenience, Ascape is designed so that these scape-level rules can be added from within the class that defines the agent. This allows us to inspect the agent and its behavioral rules in one file. Of course, these rules do not, in point of fact, belong to the agent, but to the scape in which the agent is located. When the agent class (CoordinationGamePlayer) is first created, the model will call the class's ScapeCreated() method. This method is used to add rules directly to the agent's parent scape (in this case, the 'players' scape).

```
        public void scapeCreated() {
                getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
                getScape().addRule(RANDOM_WALK_RULE);
                getScape().addRule(UPDATE_RULE);
                getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);
        }
```

First, we are going to add an *initial* rule, which is executed only on setup. This rule tells the scape to place the agents on random locations on the lattice. Then we will add three behavioral rules, which will be executed by the scape on every iteration of the model. An iteration of the model is simply an execution of the Root Scape's singe ITERATE rule. This rule activates all of the Root Scape's agents (the scape graph and the 'players' scape), and causes their rule sets to fire. The first rule for the 'players' scape simply tells the agents to move to a new, neighboring cell every turn. The agents are, in essence, doing a random walk each turn. We do not need to write any additional code for this rule. The UPDATE_RULE is an empty placeholder that calls an update() method, which we need to write. We will use the UPDATE rule as the search for the best player in the neighborhood. The PLAY_RANDOM_NEIGHBOR_RULE automatically finds a random cell occupant in the lattice neighborhood, and returns this agent to a play() method. It is up to us to write this play() method. Our play() method will take the agent that it is passed, play the coordination game with it, and then add the result to our 'recentPlays' array and update the 'totalScore' variable.

By default, the rules will be executed in the order that they are listed. This can be changed at runtime from the Settings window. For now, however, we assume that agents will initially be placed randomly, and that every iteration they will first move to a new location, then evaluate which of their neighbors to imitate, and then play the coordination game. The agents' evaluations of which neighbor to imitate will be triggered by the UPDATE_RULE, which automatically calls the update() method. So, we need to write an update() method that finds the best-scoring agent in the neighborhood, and imitates that agent.

```
        public void update() {
           count++;
           if (count > recentPlays.length)
           {
           int currScore = 0;
           int bestScore = this.totalScore;
                CellOccupant[] neighbors;
           neighbors = getHostCell().getNeighboringOccupants();
                for (int i = 0; i < neighbors.length; i++)
                  {
                     currScore = ((CoordinationGamePlayer)neighbors
    [i]).totalScore;
                     if (currScore > bestScore)
                          {
                           bestScore = currScore;
                           myColor = ((CoordinationGamePlayer)neighbors
    [i]).getColor();
                          }
                  }
                }
        }
```

First notice that this method only runs its evaluation of the neighborhood if the agent has played more than five times. This is to ensure that the value of 'totalScore' accurately reflects a full 'recentPlays' array. Thus, agents do not start imitating other agents until everyone's totalScore reflects five plays of the coordination game. An important note is that this way of writing the model assumes that the entire 'players' scape is iterated through on every turn. This is the normal procedure for a model, however we can change this procedure so that agents are chosen by random draw, or so that only a subset of the agent population is activated during an iteration of the model.

Using these latter two procedures, it is not a correct assumption that just because this agent has played five times (count > 5), that all of his neighbors have played five times. However, for now, we can safely assume that all agents will be activated on each iteration, which means that if this agent's totalScore reflects at least five plays, then so does the totalScore of his neighbors.

The agent looks around his neighborhood using the getNeighboringOccupants() method. This method cannot be called by a cell occupant, but must be called by a host cell. So, the full command first gets the host cell directly below the agent (getHostCell()), and then tells that host cell to get the neighboring occupants. The neighborhood that is surveyed is, of course, defined by the scape graph. In this case, it is a von Neumann neighborhood. The getNeighboringOccupants() call returns an array of cell occupants. We put them into an array called 'neighbors', and then iterate through the array looking for the highest value of the 'totalScore' variable. Note that the array is a CellOccupant array by default. In order to reference the 'totalScore' variable, we have to cast the contents of the array to be CoordinationGamePlayer. In summary, the agent does an uphill search on its neighbors' values for 'totalScore', and imitates the highest scoring agent in the neighborhood. Of course, the agent only changes its color if the best totalScore in the neighborhood is higher than its own.

```
public void play(Agent partner) {
   int score;
   if (((CoordinationGamePlayer)partner).getColor() == myColor)
   {
          score = 1;
   }
   else
   {
          score = 0;
   }
   updateRecentPlays(score);
}

public void updateRecentPlays(int score){
   totalScore = 0;
   for (int i = 0; i < (recentPlays.length - 1); i++){
          recentPlays[i] = recentPlays [i + 1];
          totalScore = totalScore + recentPlays[i];
   }
   recentPlays[recentPlays.length - 1] = score;
   totalScore = totalScore + recentPlays[recentPlays.length - 1];
}
```

The play() method is called by the PLAY_RANDOM_NEIGHBOR_RULE, and it takes an agent as an argument. This method simply assigns the player a score of one for coordinating with the partner agent, or a score of zero for failing to coordinate. It then calls the updateRecentPlays() method, to add the new score to the 'recentPlays' array and to update the value of the 'totalScore' variable.

The CoordinationGamePlayer Class

All told, the CoordinationGamePlayer class looks as follows:

```
public class CoordinationGamePlayer extends CellOccupant   {

    //create variables
    protected Color myColor;
    protected int totalScore;
    protected int[] recentPlays;
    protected int count = 0;

    //initialize the variables for each new agent
```

```
        public void initialize() {
              if (randomInRange (0,1) > 0)
          {
              myColor = Color.red;
            }
         else
            {
              myColor = Color.blue;
            }
              recentPlays = new int [5];
        }

        //create the list of rules for scape
        public void scapeCreated() {
              getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
              getScape().addRule(RANDOM_WALK_RULE);
              getScape().addRule(UPDATE_RULE);
              getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);
        }


        //specify the UPDATE_RULE:  imitate the most successful neighbor
        public void update() {
        count++;
        if (count > recentPlays.length)
        {
        int currScore = 0;
        int bestScore = this.totalScore;
              CellOccupant[] neighbors;
        neighbors = getHostCell().getNeighboringOccupants();
              for (int i = 0; i < neighbors.length; i++)
                    {
                    currScore = ((CoordinationGamePlayer)neighbors
[i]).totalScore;
                    if (currScore > bestScore)
                          {
                          bestScore = currScore;
                          myColor = ((CoordinationGamePlayer)neighbors
[i]).getColor();
                          }
                    }
              }
      }

      //specify PLAY_RANDOM_NEIGHBORS_RULE:  1 for coordinating, 0 for not
      coordinating. Then update the records.
      public void play(Agent partner) {
        int score;
        if (((CoordinationGamePlayer)partner).getColor() == myColor)
        {
              score = 1;
        }
        else
        {
```

```
                    score = 0;
                }
                updateRecentPlays(score);
            }

            // Update the record of wins, and the totalScore
            public void updateRecentPlays(int score){
                totalScore = 0;
                for (int i = 0; i < (recentPlays.length - 1); i++){
                    recentPlays[i] = recentPlays [i + 1];
                    totalScore = totalScore + recentPlays[i];
                }
                recentPlays[recentPlays.length - 1] = score;
                totalScore = totalScore + recentPlays[recentPlays.length - 1];
            }
                //Standard getColor method
                public Color getColor() {
                    return myColor;
            }

        }
```

The CoordinationGame class combined with the CoordinationGamePlayer class define a complete Ascape Coordination Game Model.

So, in summary :

To create the model class:

1) create the variables
2) create the scapes and the agents
3) create the views
4) populate the model with agents

To create the agents class:

1) create the variables
2) initialize the agent
3) add rules to the scape
4) specify the contents of the rules

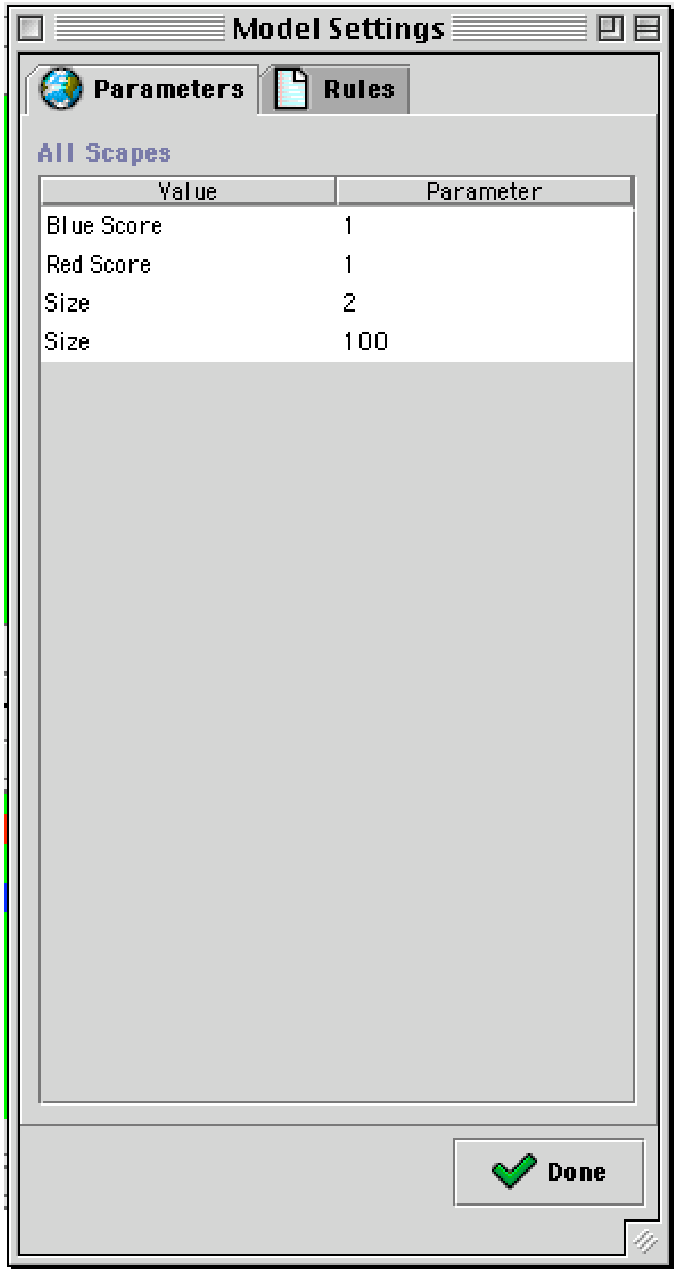
Cleaning up the Model

You will notice that the payoff matrix for this coordination game is completely symmetrical. There is no dominant strategy. A user of the model may wonder what would happen if we changed the payoffs so that coordinating on red gave a reward of 2, while coordinating on blue only gave a reward of 1. In the current design of the model, we must change the code inside the agent class in order to run this experiment. As we saw above, properties of the scapes (e.g., the rules) are accessible to the user through the Settings window. Additionally, properties of the model (model-scope variables) are also available for the user to edit through the Settings window. The nPlayers variable, the lattice_height variable, and the lattice_width variable can all be changed by the user at runtime. Similarly, we can create variables in the model class, say 'coordinateOnBlue' and 'coordinateOnRed', that the user can edit in the Settings window. Instead of hard-coding the payoffs into the agent class (as we did above), we can use these variables to determine the agents' payoffs for coordinating on blue or red. Thus, the users can experiment with the dynamics of the model by changing the value of these variables at runtime. In fact, good coding practice for Ascape in general is to make important variables part of the model class. These variables can then both be accessed by the agents and edited by the user, giving the user dynamic control over the behavior of the agents.

In order for model variables to appear in the Settings window, and for the user's changes to them to take effect in the model, the developer must write get() and set() methods for these variables. When the Settings window is opened it automatically looks for all available get() methods of model-scope variables and populates itself. Similarly, when changes are made in the Settings window, the set() method is automatically called to update the model while it runs. So, to add user control over the payoff matrix, we will first add our new variables to the model and then we will add the get() and set () methods.

```
public class CoordinationGame extends Scape {

        public int nPlayers = 200;
        public int latticeWidth = 30;
        public int latticeHeight = 30;

        //new variables for coordination on Red and Blue
        public int coordinateOnBlue = 1;
        public int coordinateOnRed = 1;
        .
        .
        .

        public int getRedScore(){
                return coordinateOnRed;
        }

        public void setRedScore(int NewcoordinateOnRed){
                coordinateOnRed = NewcoordinateOnRed;

        }

        public int getBlueScore(){
                return coordinateOnBlue;
        }

        public void setBlueScore(int NewcoordinateOnBlue){
                coordinateOnBlue = NewcoordinateOnBlue;
        }
```

The method getRedScore() reports the value of the variable 'coordinateOnRed', allowing it to show up in the Settings window. The method setRedScore() changes the value of 'coordinateOnRed' to the value entered in the Settings window. setRedScore() is automatically called by the Settings window when the user edits the 'RedScore' variable. The model must have get() and set() methods for any variable that the developer wants the user to be able to edit from the parameters window.



Value	Parameter
Blue Score	1
Red Score	1
Size	2
Size	100

Fig.30: Parameters Window with new variables.

Now that the user can access these variables, the agents need to be able to access them, too.

```
public void play(Agent partner) {
       int score;
       if ((((CoordinationGamePlayer)partner).getColor() == myColor) && (myColor
== Color.blue))
       {
              score = ((CoordinationGame)getModel()).getBlueScore();
       }
   else if ((((CoordinationGamePlayer)partner).getColor() == myColor) &&
(myColor == Color.red))
       {
              score = ((CoordinationGame)getModel()).getRedScore();
       }
       else
       {
              score = 0;
       }
       updateRecentPlays(score);
   }
```

Notice that in order to reference the getRedScore() method, we need to call the getModel() method, and then cast it to the CoordinationGame model. This call returns the Root Scape for the model, but it returns it as a Scape object, which must be cast to a CoordinationGame object in order to reference the desired get() method. This kind of casting procedure is fairly common in Ascape since the Ascape calls return basic data structures (such as Scapes) which need to be cast to the specific type of object that the developer is using (e.g., the CoordinationGame Scape).

In order to inspect an agent's properties when a model is running, you can ALT + click on the agent and an Agent Inspection window will appear. This window will display the agent's parameters with their current values. Just like in the model's Settings window, the variables that are displayed in the Agent Inspection window are the ones that have get() and set() methods for them. Analogously to the methods used to get and set model variables, get() and set() methods for agent variables are usually put at the end of the agent class. As a rule of thumb, it is useful to write get() and set() methods for most of your agent variables so that you can inspect them as the model is running. This is very helpful for debugging models.

Adding Statistical Operations

Statistical operations are a useful way of gleaning information from the model. Like the views discussed above, statistical operations are windows into scapes. The difference in the case of the statistical operation is that instead of operating on just the scape graph, they operate on every kind of scape. In general, stats are added to scapes to provide detailed information about the properties of their members. To take a basic example from the Coordination Game Model, let us collect a statistic on the number of agents that are red and blue at any given time. This statistical operation is window into the ‘players’ scape. All of the code for the statistical operations is within the createScape() method.

```
        public void createScape() {
    ...

            StatCollector CountReds = new StatCollectorCond("Reds") {
                public boolean meetsCondition(Object object) {
                    return (((CoordinationGamePlayer) object).myColor ==
    Color.red);
                }
            };
            StatCollector CountBlues = new StatCollectorCond("Blues") {
                public boolean meetsCondition(Object object) {
                    return (((CoordinationGamePlayer) object).myColor ==
    Color.blue);
                }
            };

            players.addStatCollector(CountReds);
            players.addStatCollector(CountBlues);
        }
```

First, we create the objects that will hold the statistics. One is called 'CountReds', the other is called 'CountBlues'. In order to make these objects, we need to specify a kind of statistical operation. In this case, we use a simple conditional statistical operation, called StatCollectorCond: if an object in the scape meets the condition (i.e., returns 'true'), then it is included in the statistic. In this case, the condition is that the object is a certain color. The first statistical operation counts all of the red agents, and the second one counts all of the blue agents. Once these operations are defined, they are added to the players scape.

When the model runs, it will perform the 'CountReds' and 'CountBlues' operations every iteration. In order to see these stats, we need to add a chart to the model; a chart is a window that displays statistics. There are two ways to do this. First, one can create a chart at run time, using the Ascape Toolbar to select the chart dialog box. The user can then select whether to view the stats as a time series, a histogram, or a pie chart. Also, the user can dynamically assign colors to the stats.

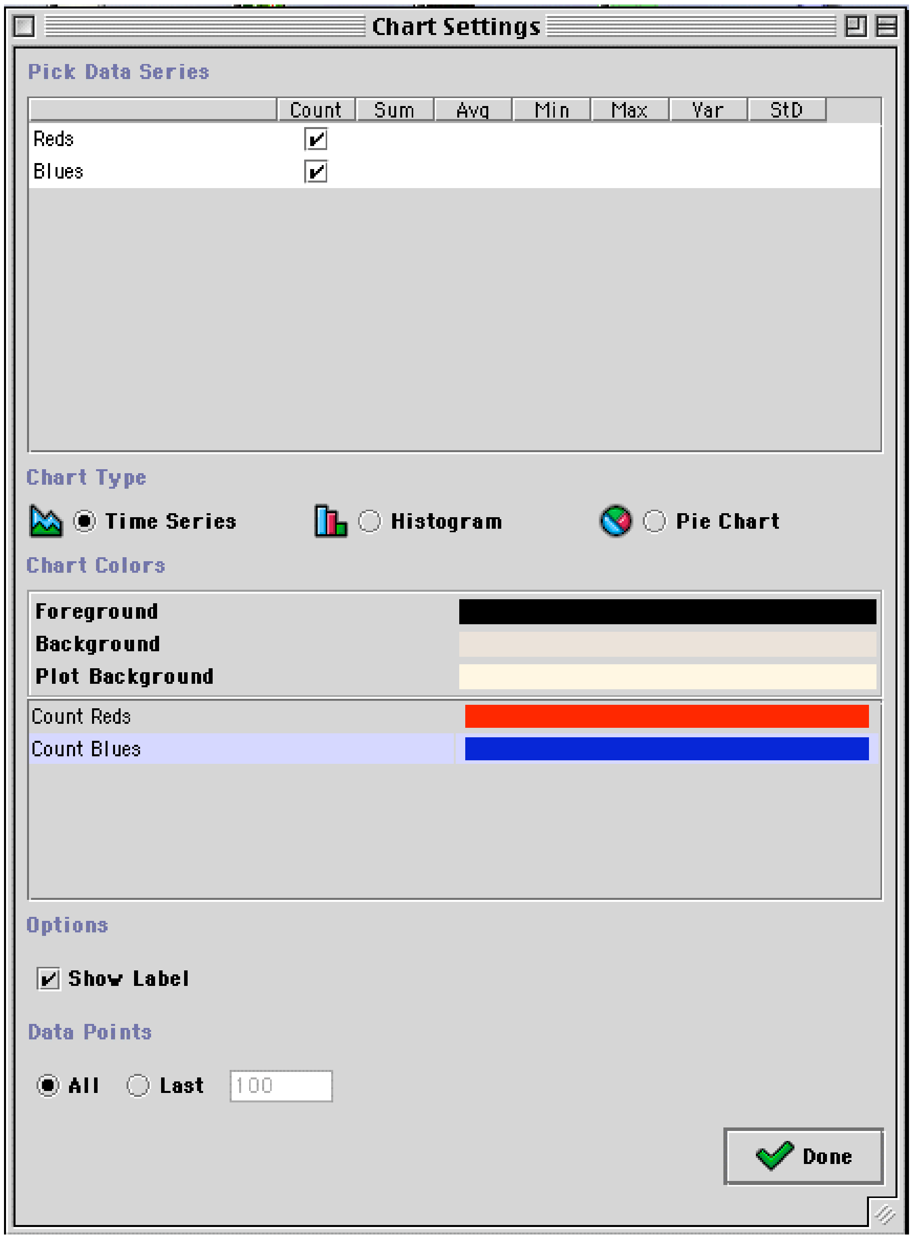


Chart Settings

Pick Data Series

	Count	Sum	Avg	Min	Max	Var	StD
Reds	✓						
Blues	✓						

Chart Type

[✓ Time Series] Histogram Pie Chart

Chart Colors

Foreground	⬛
Background	⬜
Plot Background	⬜
Count Reds	🟥
Count Blues	🟦

Options

[✓] Show Label

Data Points

[✓ All] Last 100

Fig.31: Creating a chart at runtime.

This is the easiest way to add a chart to the model in which to view the statistics that you have created. However, if you create your chart this way, it goes away when the model closes. These 'runtime' charts need to be created using the dialog box every time the model is opened. If you want a chart to launch with the model, you can specify all of the same information that is in the dialog box in the content of the createGraphicViews() method. This will create a new chart window and fill it with your stats when the model launches. Of course, the content of this window can also be edited at runtime from the chart dialog box.

To add a chart to the model this way, we need to create a chart, add the stats, and specify the plotting dimensions.

```
public void createGraphicViews() {
        .
        .
        .
        ChartView chart = new ChartView();
        players.addView(chart);
        chart.addSeries("Count Reds", Color.red);
        chart.addSeries("Count Blues", Color.blue);
        ((TimeSeriesViewModel)chart.getViewModel()).setDisplayPoints(100);
}
```

First, we create a new chart and add it to the 'players' scape. Then we add each of the stats to the chart. The stats can be graphed in a number of ways, but we are choosing to graph them as a time series. So, we use the chart.addSeries() method. The first argument to this method gives both the operation being performed (Count) and the name of the stat (Reds) in a single string. We use a string, instead of two arguments, so that this parameter can be used as the label for this series on the chart. So, the "Count Reds" label, will be attached to a time series that graphs the count (number of agents) that satisfy the "Reds" statistical operation. The second argument tells the chart to use the color red to chart this series. Similarly, we do the same for the "Blues" stat. Finally, we set the dimensions of the chart to show 100 iterations, or time steps, along the horizontal axis.

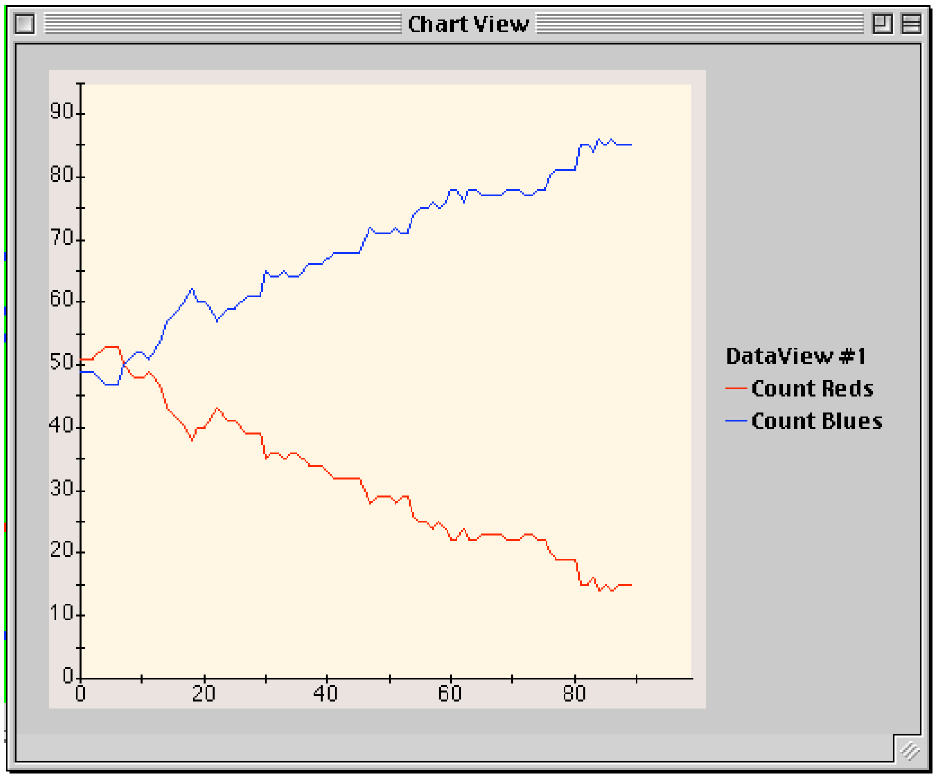


Fig.32: Chart View with new statistics

We are now finished writing the Coordination Game Model. In the next part of the tutorial, we will see how Ascape allows us to experiment with the model by changing / adding parameters, adding statistics, and changing the agent dynamics. See the appendix for the complete source code of the model.

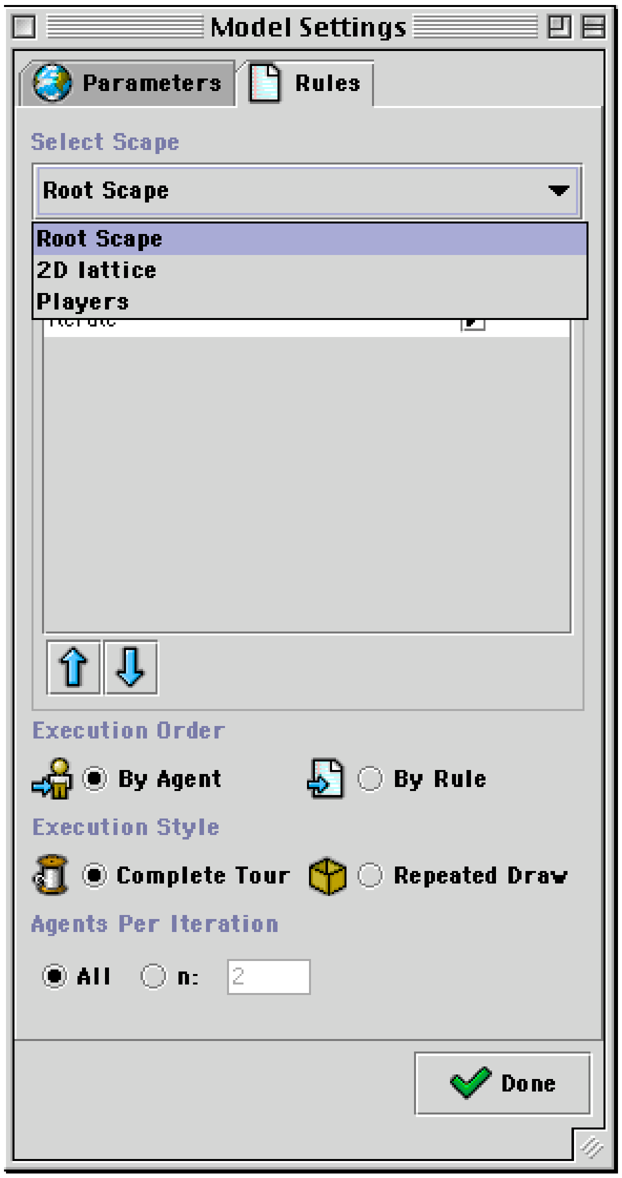
Experimenting with the Model

Editing Model Properties at Runtime

We have already seen that we can change a scape's rules, and a model's parameters at runtime. But, we can also change whether a scape executes its rule synchronously or asynchronously, and whether a scape iterates through all of its agents, or picks random agents on every iteration of the model. These parameters can all be set from within the Ascape code, but they can also be edited on the fly in the Settings window.

The Rules Tab

All of the properties listed in the rules tab are relevant to the scape that is selected in the 'Select Scape' menu at the top of the window. In the base case, there are three scapes that one can choose from: the Root Scape (i.e., the Model), the Scape Graph (e.g., 2D lattice), and whatever scape contains the agents (e.g., Players). If there are more scapes, or sub-scapes, these will appear in the list as well.



Select Scape: Root Scape

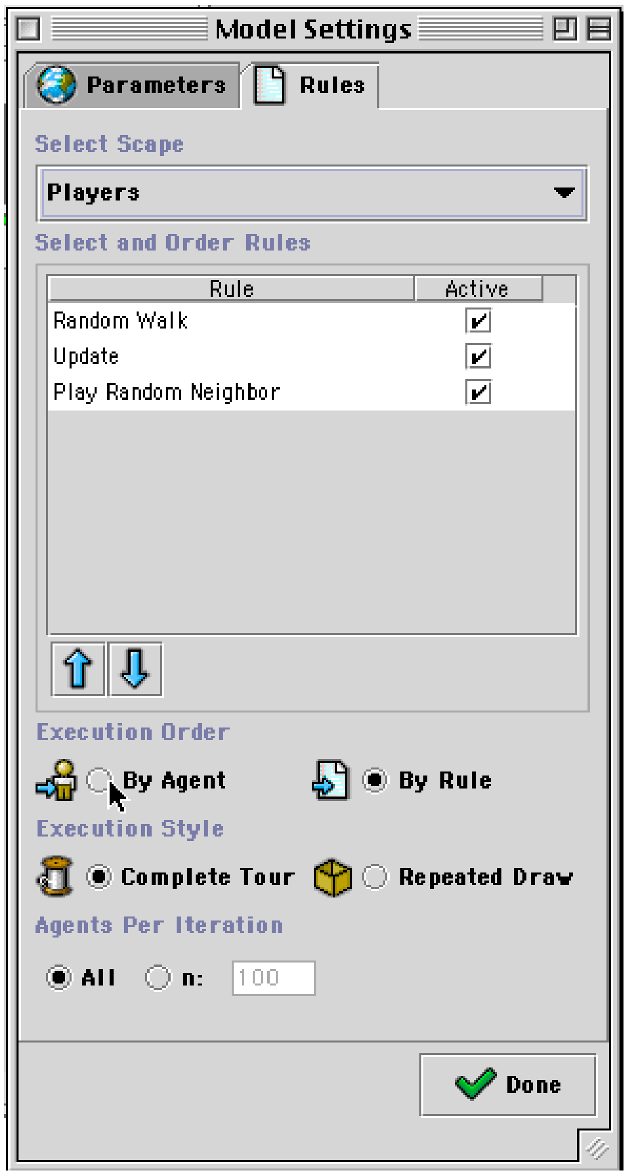
Execution Order: [✓ By Agent] By Rule

Execution Style: [✓ Complete Tour] Repeated Draw

Agents Per Iteration: [✓ All] n: 2

Fig.33: Settings Window (pull down of scapes)

Once a scape is chosen, the 'Select and Order Rules' panel will display all of the rules that are part of the scape. They are displayed in the order in which they are executed. Each rule can be checked or unchecked (making it active or inactive in the current run of the model). And, if a rule is selected, it can be moved earlier or later in the execution order by clicking on the up and down arrows.



Select Scape

Players

Select and Order Rules

Rule	Active
Random Walk	✓
Update	✓
Play Random Neighbor	✓

Execution Order

[ ] By Agent [● By Rule]

Execution Style

[● Complete Tour] [ ] Repeated Draw

Agents Per Iteration

[● All] [ ] n: 100

Fig.34: Settings window (editing rule order)

The ‘Execution Order’ radio buttons allow the user to select whether the model will run synchronously or asynchronously. Intuitively, the ‘By Agent’ option is asynchronous, and the ‘By Rule’ option is synchronous. The ‘Execution Style’ radio buttons determine whether the scape iterates through all of its members every iteration, or whether it picks random agents. In the latter case, it may well happen that during an iteration of the model some agents are randomly chosen more than once, and some agents are not chosen at all. Finally, the ‘Agents per Iteration’ radio buttons determine how many of a scape’s agents it iterates through during one step of the model. If the players scape is selected, then it can either activate ‘All’ of its members (i.e., 100), or it can activate some number between 0 and 100.

In base case for the Coordination Game Model, the 2D lattice scape does not have any agents, so its setting is irrelevant. The Root Scape has 2 agents: the 2D lattice scape and the players scape. By default the Root Scape only has 1 rule: ITERATE. This rule simple tells the scape to activate each of its sub-scapes. Since the Root Scape only has one rule, it is irrelevant whether it is set to execute in Agent Order or in Rule Order. In either case, the 2D lattice and the 'players' scape will both be activated in the same way. The Execution style for the Root Scape should always be Complete Tour, otherwise an entire scape of agents could be omitted from an iteration of the model. And, for similar reasons, the Agents Per Iteration is generally set to 'All'.

The Players scape has three rules, and we can mix their order, or turn them off. But, for now, we will experiment with the other scape settings. We coded the players scape to execute in RULE_ORDER. By default it will execute a complete tour of all the agents. This default setting ensures that all agents will be activated during each iteration of the model. However, if 'Agents Per Iteration' is set to 'n: 50', 'Execution Style' is set to Repeated Draw, and 'Execution Order' is set to 'By Agent'. Then instead of iterating through each rule for each agent, the model with pick a random agent, iterate through all of its rules, and then pick another agent (possibly that same agent again). Since we set 'Agents Per Iteration' to 50, the model will pick 50 times, and then start a new iteration. But, you can easily see that we quickly lose the significance of the end of one iteration and the beginning of another. Since the only scape, besides the Root Scape, with active agents is the players scape, the model runs like a continuous random selection of agents (making the 'Agents Per Iteration' parameter essentially irrelevant).

Try experimenting with the model under these conditions, notice that the model still converges, but takes much longer to do so. For any model, it is important to test its behavior under conditions of synchronous / asynchronous updating, and complete tour / repeated draw. They are important tests for robustness and model validation. Similarly, activating/deactivating and changing the order of rules at runtime can be a useful way of experimenting with the dynamics of complex models in which multiple scapes have agents with multiple rules.

Adding Stochasticity to the Model

Now that we have seen some of the ways that we can experiment with the behavior of the Coordination Game Model, we can begin to expand on the model by adding more interesting behavior to the agents. One easy way to do this is to introduce some stochasticity into the model. In the current model, agents always choose to imitate the color that is the most successful in their neighborhood. Although this makes sense, we may wonder what would happen if we added some noise to this decision-making process – so that 10% of the time agents would choose randomly. We can run this experiment by adding a variable to the model called 'error'. Then we say that with the probability of 'error', an agent will not choose to imitate the best in the neighborhood, but will choose its color randomly. We will make 'error' a model-scope variable, so that we can edit it from the Settings window and see how the model behaves under different error rates.

First, we add the variable 'error' to the CoordinationGame class, with get() and set() methods so we can access it from the Settings window.

```
public class CoordinationGame extends Scape {

    protected int nAgents = 100;

    protected int latticeWidth = 30;

    protected int latticeHeight = 30;

    public int coordinateOnBlue = 1;

    public int coordinateOnRed = 1;

    //new variable
    public int error = 0;

    Scape lattice;

    Scape agents;

    Overhead2DView overheadView;
    .
    .
    .

    //get and set methods
    public int getError(){
             return error;
    }

    public void setError(int NewError){
             error = NewError;
    }

}
```

Next, we change the update() rule in the CoordinationGamePlayer class to include the possibility of error. The error variable determines the percentage of the time that the agent will choose randomly instead of imitating the best in the neighborhood.

```
public void update() {
       count++;
       if (count > recentPlays.length)
       {

             //if the random number between 1 and 100 is greater than,
             or
             //equal to 'error', proceed as normal
             if (randomInRange(0,100) >= ((CoordinationGame)getModel
()).error)
             {
                    int currScore = 0;
                    int bestScore = this.totalScore;
                    CellOccupant[] neighbors;
                    neighbors = getHostCell().getNeighboringOccupants();
                           for (int i = 0; i < neighbors.length; i++)
                           {
                           currScore = ((CoordinationGamePlayer)neighbors
                           [i]).totalScore;
                              if (currScore > bestScore)
                              {
                               bestScore = currScore;
                                myColor =   ((CoordinationGamePlayer)
                                neighbors[i]).getColor();
                               }
                           }
             }
             //otherwise, choose randomly
```

```
                    else
                    {
                            if (randomInRange (0,1) > 0)
                            {
                                    myColor = Color.red;
                     }
                            else
                             {
                            myColor = Color.blue;
                             }

                    }

            }
    }
```

Error is initially set to 0, but we can open the Settings window and change it to, say, 10. If we wait until the model converges, and then change the 'error' value, we see about ten percent of the population jump out of convergence.

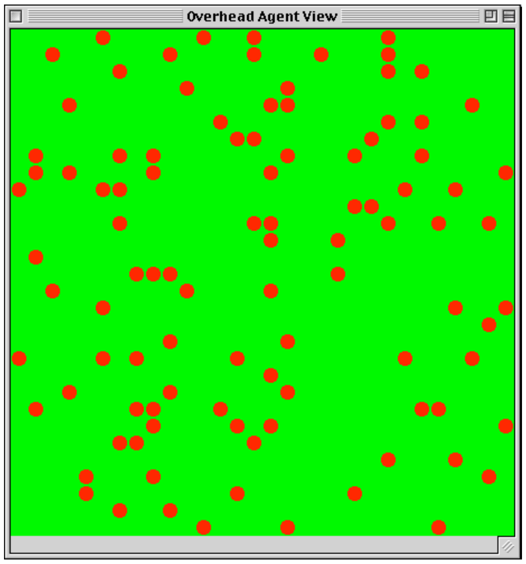
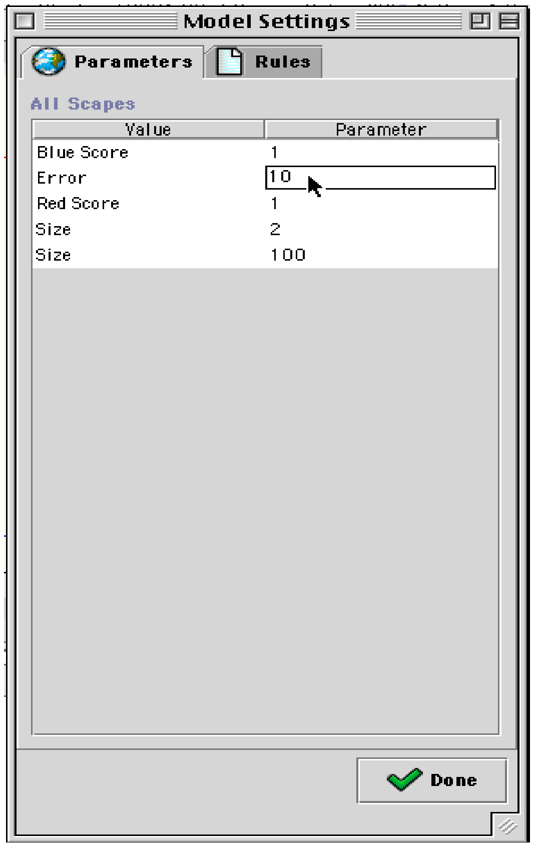


Fig.35: Model converging



All Scapes

Value	Parameter
Blue Score	1
Error	10
Red Score	1
Size	2
Size	100

Fig.36: Settings window (introducing error)

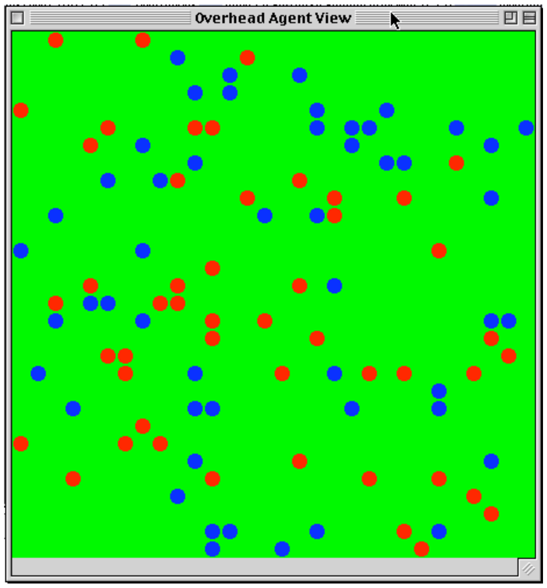


Fig.37: Model 'shocked' with error

Once we 'shock' the model with an error rate greater than 0, we can reset the value of error to 0, and watch to see if the model switches equilibria and converges to a different color. We can experiment with population sizes and error rates to see what value of error is needed to 'bump' a model from one equilibrium to another.

Stochastic Stability

Also, instead of changing the error rate back to 0 once the model has been shocked, we can leave the error at the new rate. If we run the model this way, the population will never converge, and it will simply exhibit a pattern of noisy interactions. An interesting experiment to run at this point is to change the payoff matrix so that it is asymmetrical. With the Settings window already open, we can simply change, say, the value of RedScore from 1 to 2. Now, the model should quickly converge on all red. However, if we keep a constant error rate in the model, we should always see a small population of blue agents. At this point, the model will show a 'stochastically stable' heterogeneous population of agents. The ratio of reds to blues will depend on the payoff matrix and the error rate, but we can see that simply by adding error, the simple coordination game shows a complex, but stable, pattern of agent behavior.

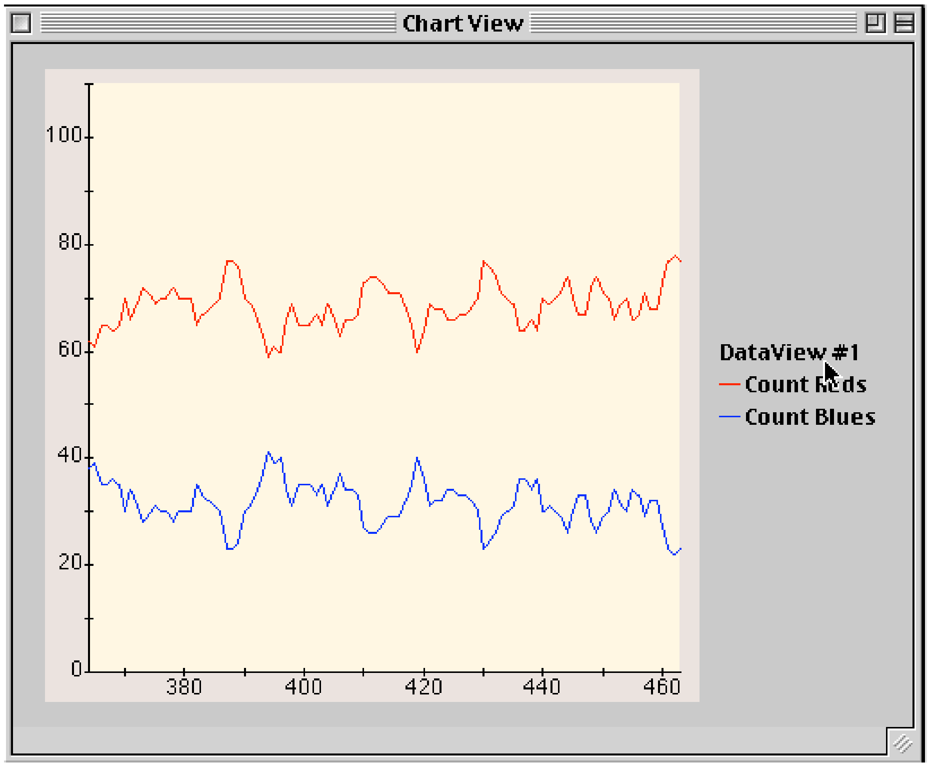


Fig.38: Asymmetrical Payoffs with Constant Error

Adding Averaging Statistics to the Model

Now that we have added a bit more complexity to the model, we may be interested in how this affects the payoffs of the agents. In the case where error = 0 and payoffs are symmetric, we know that the model will converge so that everyone will receive the same payoff of 1 every turn. We may wonder, however, whether in the case where error = 10 and red payoff = 2, whether the society has higher overall welfare or lower overall welfare than the base case. Because of the increased payoff for red coordination, the red agents will certainly have a higher welfare than any of the agents in the base model. However, because of the frequent errors, many agents will also receive a 0 payoff for miscoordination. So, we many want a new statistic that will tell us the overall welfare of the society, so that we can compare the model with error and asymmetric payoffs to the model with no error and symmetric payoffs.

To add the new statistic to the CoordinationGame class, we follow the same coding pattern used earlier, but this time we will not use the StatCollectorCond Stat Collector class, because we do not have a condition that needs to be satisfied. Rather, we want to collect data from every agent, and then to average this data over the total number of agents. To do this, we use the StatCollectorCSAMM class, which allows us to perform averaging operations on the data it collects. So, we go the createGraphicViews() method in the CoordinationGame class.

```
        public void createGraphicViews(){
            .
            .
            .
            //create stat collector that will get payoff information
            StatCollector AvgPayoff = new StatCollectorCSAMM("Payoff") {
                  public double getValue(Object object) {
                     return ((CoordinationGamePlayer) object).getRunningTotal
    ();
                  }
           };
            .
            .
            .
            //add stat collector to the players scape
            players.addStatCollector(AvgPayoff);

            //add average payoff series to the chart
            chart.addSeries("Average Payoff", Color.black);

            }
```

First, we create the stat collector 'AvgPayoff', using the class StatCollectorCSAMM. We label this statistic "Payoff". The method getValue() calls the getRunningTotal() method inside CoordinationGamePlayer, which will return the totalScore variable that each CoordinationGamePlayer agent has. This is a standard get() method, like the ones used above, which we will need to add to the CoordinationGamePlayer class. It will allow us to retrieve each agent's totalScore so that they can be summed and averaged by the StatCollectorCSAMM class. Once the statistic is created, we add it to the 'players' scape. We can add this statistic to the chart already created in the createGraphicViews() method or to a chart at runtime using the chart dialog box. We will add it in the code so that all three statistics appear when the model opens. We add it to the chart as time series that performs an averaging operation (i.e., we call it "Average Payoff"). Once we add the getRunningTotal() method to the CoordinationGamePlayer class, we can watch this stat run.

```
    public class CoordinationGamePlayer extends Cell Occupant{
            .
            .
            .
            public int getRunningTotal(){
                  return (totalScore * 10);
            }
    }
```

The getRunningTotal() method returns the 'totalScore' variable multiplied by 10. We use this increased magnitude simply to make small fluctuations in the average value of 'totalScore' visible in the time series. Intuitively, the base model will converge to one color, and the 'totalScore' variable will converge to 5 (since there is a memory that is 5 plays long, and every play, after convergence, should produce a 1 for everyone). This will display on the chart as a line at the value 50.

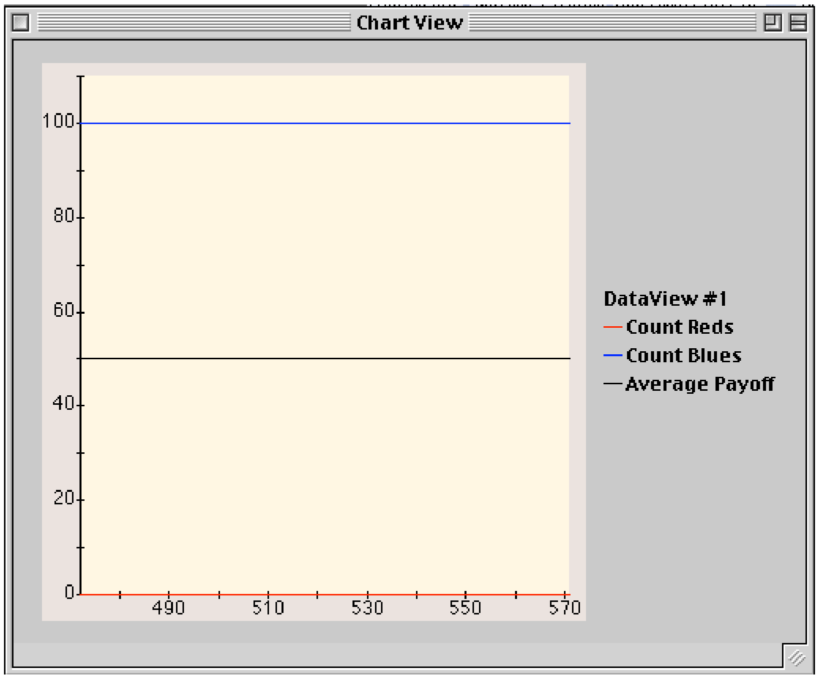


Fig.39: Base Model with Payoff graph.

If we add error to the model, and increase the red payoff, we see that the average payoff spikes and then fluctuates around 75. So, in the main, social welfare is higher when there is a small degree of error and a high asymmetric payoff, than when there is no error and a low symmetric payoff.

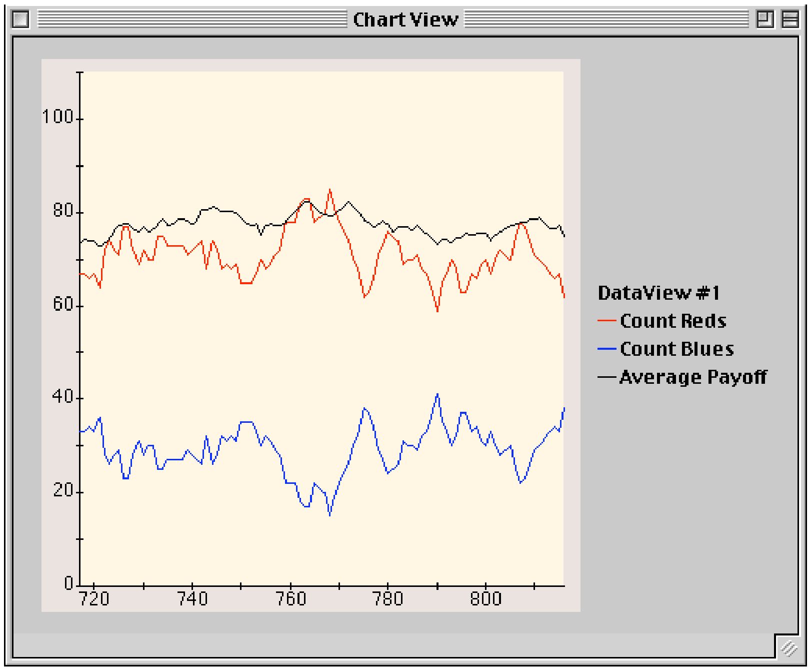


Fig.40: Stochastic Model with Payoff Graph

This result seems consistent with our intuitions, but the graph is useful because it clearly shows how social welfare varies with changes in error rate and payoffs. So, now we can experiment with the parameter values to see how much error the higher payoff asymmetry can sustain before payoffs start to dip below the payoffs for the symmetric model. Significantly, all of these experiments can be made while the model is running (in the Settings window), without having to change any code.

Best Reply Dynamics

The Coordination Game that we have been developing uses imitation as the basic behavioral rule. However, after we have experimented with this model, we may want to explore other rules for coordinating agents. A common one is best reply. Using a best reply rule, agents keep a record of their opponents' strategies in previous plays, and then they decide what to play by determining what is a best reply to the majority of opponent strategies that they have encountered. In the symmetric payoff Coordination Game, the best reply is simply to play the same color that has made up the majority of an agent's interactions. However, the expected payoff of a decision is the likelihood of an outcome (in this case, the frequency of a color in an agent's history) times the payoff for that outcome. So, in an asymmetric game, we must factor the payoff matrix into the agent's decision.

In order to make the Coordination Game Model into a best reply model, we must rewrite the update() method (the contents of the UPDATE rule), so that agents will use the history of their partners' decisions to decide what color to play. So in addition to the 'recentPlays' array, we need a second array that will keep a record of the colors that the agents' partners have played; let us call it the 'recentPartners' array. The update() method will walk through the 'recentPartners' array, find the frequency of red and the frequency of blue, and multiply these frequencies by the payoffs for coordinating on red and coordinating on blue. Whichever value is larger will be the color that the agent will play. At the start, these payoffs are both 1, so this last operation has no effect. However, we will build it into the model so that once we start experimenting with payoff parameters, the agents will be equipped to make the correct evaluations.

All the changes for the best reply model take place in the CoordinationGamePlayer class.

```
public class CoordinationGamePlayer extends CellOccupant   {
       protected Color myColor;
       protected int totalScore;
       protected int[] recentPlays;
       protected int count = 0;

       //add the partners array
       protected Color[] recentPartners;
       //add variables to hold the running totals of reds and blues in
       the //partners array
       protected int totalreds;
       protected int totalblues;


//we use the random choice algorithm three times in this class, so to
keep
//things tidy, I have made it a separate method, called 'doRandom()'
public void doRandom(){
             if (randomInRange (0,1) > 0)
                 {
                   myColor = Color.red;
```

```
                }
                else
                {
                myColor = Color.blue;
                }
        }

    //each time the agent plays, it updates the score array (recentPlays), 
    and
    //also updates the recentPlayers array.
    public void play(Agent partner) {
            .
            .
            .
            updateRecentPlays(score);
            updateRecentPartners(((CoordinationGamePlayer)partner).getColor
    ());
        }

    //the agents update the recentPartners array with the color of the most
    //recent player, and also keep a running total of red and blue partners
    public void updateRecentPartners(Color ncolor){
            totalreds = 0;
            totalblues = 0;
            for (int i = 0; i < (recentPartners.length - 1); i++){
                    recentPartners[i] = recentPartners [i + 1];
                            if (recentPartners[i] == Color.red)
                                    {
                                            totalreds = totalreds + 1;
                                    }
                            else if (recentPartners[i] == Color.blue)
                                    {
                                            totalblues = totalblues + 1;
                                    }
            }
            recentPartners[recentPartners.length - 1] = ncolor;
            if (ncolor == Color.red)
                    {
                            totalreds = totalreds + 1;
                    }
            if (ncolor == Color.blue)
                    {
                            totalblues = totalblues + 1;
                    }
        }

    //The update method is where the agent decides what to play.  The 
    agent //multiplies the number of reds in its recent history by the payoff 
    for red //coordination, and the number of blues by the payoff for blue 
    coordination.  //Whichever number is largest determines the agent's next 
    play.  If the 
    //values are tied, the agent chooses randomly.  Also, I have left the 
    error 
    //code in the update method, so that we have the option of experimenting 
    with //errors in the best reply model.
    public void update() {
        count++;
        if (count > recentPlays.length)
        {

              if (randomInRange(0,100) >= ((CoordinationGame)getModel
   ()).error)
              {
                int redScore;
                int blueScore;
                blueScore = totalblues * ((CoordinationGame)getModel
   ()).getBlueScore();
                redScore = totalreds * ((CoordinationGame)getModel
   ()).getRedScore();
                if (redScore > blueScore)
                     {
                           myColor = Color.red;
                     }
                else if (blueScore > redScore)
                     {
                           myColor = Color.blue;
                     }
                else
                     {
                           doRandom();
                     }

              }
              else
              {
                     doRandom();
              }
        }
  }
```

Since our agents will be ‘boundedly rational’ agents, the ‘recentPartners’ array should be relatively small. I have chosen to keep the ‘recentPlays’ array and the ‘recentPartners’ array to a length of 5. Experimenting with this value can also change the dynamics of the model. As above, we can also experiment with the best reply dynamics by making the ‘error’ variable positive, and by changing the payoff matrix.

A Biological Coordination Game

A different direction to take the Coordination Game Model is to eliminate decision making altogether and make it an evolutionary game theoretic model. To do this, we need to replace the imitate and best reply rules with reproduction and death rules. In the biological model, agents reproduce when their score gets to a certain value (say, 5), and then their score is reset to 0. As agents keep coordinating, they keep reproducing. Agents who fail to coordinate (e.g., who have a score of 3 or less after 5 turns) die off. While in the previous model, agents could change color based on their best options, in this model, agents are fixed as either blue or red, and the evolutionary dynamics determine which ‘genotype’ will survive.

To make the Coordination Game Model into a biological model, we will need to change the rule set for the ‘players’ scape. Players will no longer call an UPDATE rule to evaluate their best options. Rather, they will play, and then they will call a METABOLISM rule to determine whether they should reproduce or they should die. We will add a few new variables (e.g., 'repScore' and 'minScore') as constraints on reproduction and death. We will make these variables model-scope variables with get () and set() methods, so that we can experiment with different values for reproduction and death to see how they affect the dynamics of the model.

These changes to the Coordination Game Model primarily take place in the class CoordinationGamePlayer, except for the addition of new model-scope variables, which are added to the CoordinationGame class.

```
public class CoordinationGamePlayer extends CellOccupant   {
        .
        .
        .
        //we remove the UPDATE rule, and add a METABOLISM rule, which
        calls the
        //metabolism method, added below.
        public void scapeCreated() {
               getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
                getScape().addRule(RANDOM_WALK_RULE);
                getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);
                getScape().addRule(METABOLISM_RULE);
        }

        //The metabolism() method (called by the METABOLISM rule)
        evaluates on
        //the totalScore variable.  If totalScore equals 'repScore', then
        the
        //agent reproduces.  Initially, 'repScore' will be set to 5, but
        it can
        //be changed in the Settings window.
        public void metabolism(){
        if (totalScore == ((CoordinationGame)getModel()).getrepScore())
        {
                count = 0;
                        reproduce();
                for (int i = 0; i < (recentPlays.length - 1); i++){
                        recentPlays[i] = 0;
                }
        }
        //If the totalScore variable is less than the repScore, then the
        agent //evaluates whether it should die.  If the agent's total
        score is less than //the MinDieScore, and the agent has been
        through 'TurnstoDie' number of //turns, then the agent dies.
        Initially, the 'MinDieScore' is 3, and the //'TurnstoDie' is 5.
        So, if the agent is not successful in coordinating more //than 3/5
        of the time, then it will die.
        else if (totalScore <= ((CoordinationGame)getModel
()).getMinDieScore() && count >= ((CoordinationGame)getModel
()).getTurnstoDie())
        {
                this.die();
        }
     }

//To reproduce, the agent first makes sure that there is a neighboring
spot
```

```
//where the baby can be placed.  So, agent reproduction is constrained by
the //density of the neighborhood.  If there is a space, we create a new
agent, //called 'baby', of type CoordinationGamePlayer.  We add this
agent to the //'players' scape, so that it will have all of the rules
that are owned by
//the scape, and it will live on the 'lattice' scape graph.  We
initialize
//the new agent to set its basic properties, but then we explicitly set
its
//color to match the parent's color (because the initialize() method sets
the //color randomly).  Finally, we place the new, initialized agent onto
the //lattice.
public void reproduce(){
        if(this.getHostCell().isNeighborAvailable())
        {
              CoordinationGamePlayer baby = (CoordinationGamePlayer)
this.clone();
             ((Scape) this.getScape()).add(baby);
              baby.initialize();
              baby.setColor(myColor);
              baby.moveTo(this.getHostCell().findRandomAvailableNeighbor
());
        }
    }
```

There are two final changes to CoordinationGamePlayer class. First, the reproduction() method calls a setColor() method. This is used to set the color of the baby to the color of the parent. We need to create this method.

```
public void setColor (Color NewColor){
       MyColor = NewColor;
}
```

Second, since we are using the count variable to determine how many plays an agent has been through, we need to add a line of code to the play() method that increments 'count' every time the agent plays an opponent.

```
public void play (Agent partner){
       .
       .
       .
       count = count + 1;
}
```

Finally, we need to add our new model-scope variables to the CoordinationGame class, with get() and set() methods.

```
public class CoordinationGame extends Scape {
    .
    .
    .
    public int turns = 5;

    public int repScore = 5;

    public int minScore = 3;
```

```
.
.
.
  public int getTurnstoDie(){
              return turns;
  }

  public void setTurnstoDie(int Newnum){
              turns = Newnum;

  }

  public int getrepScore(){
              return repScore;
  }

  public void setrepScore(int Newscore){
              repScore = Newscore;

  }
  public int getMinDieScore(){
              return minScore;
  }

  public void setMinDieScore(int Newscore){
              minScore = Newscore;

  }
```

The biological version of the Coordination Game Model exhibits interesting spatial behavior. As agents successfully reproduce, they build dense neighborhoods of same-color neighbors. These neighborhoods rapidly spread until the entire lattice is covered with agents. The neighborhood that grows the fastest has more members, and so has more agents trying to reproduce. The border areas between the two neighborhoods are areas of 'low fitness', and these agents are constantly dying off. Since the larger group has more agents vying for reproductive space, its agents fill the border areas more quickly than the smaller group. Soon, the smaller group is run to extinction, and the population fixates on one color.

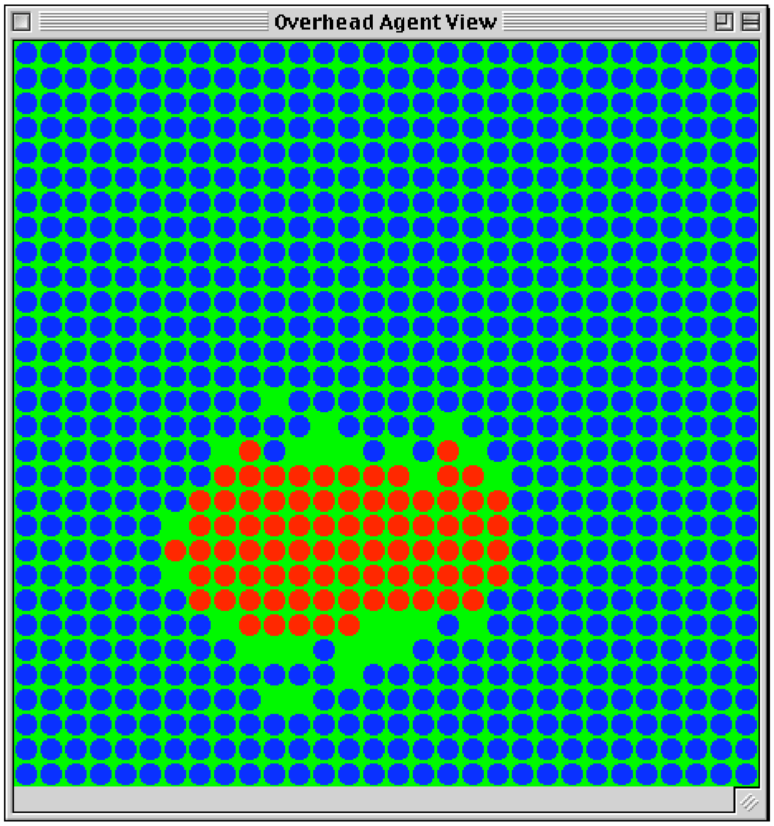


Fig.41: Biological Coordination Game Model

As in the previous versions of the Coordination Game Model, we have used model-scope variables so that the user can explore the dynamics of the model without having to edit the code. Also, the developer can easily add a few lines of code to introduce error into the reproduction process, essentially adding 'mutation' to the model.

Dynamic neighborhoods and social networks

Let us step back from the biological, or reproduction, version of the Coordination Game, and return to the earlier versions with decision theoretic agents. In those versions of the Coordination Game Model, all of the interactions were spatially localized. The PLAY_RANDOM_NEIGHBOR rule automatically uses the geometry of the scape graph to assign partners. Looked at from a networks perspective, using the model's von Neumann geometry to assign playing partners is tantamount to creating a dynamic partners network. Also, using the local neighborhood as the basis for evaluating the best player to imitate creates a dynamic imitation network. These social networks overlapped because they were using the same Von Neumann neighborhood. The partners network and imitation network are both dynamic because the cgplayer agents are moving each turn, so that the actual members of the neighborhood changes every iteration of the model. As we have seen, using the local neighborhood to determine the contents of the partners network and the imitation network produces interesting consequences for the 'demographics' of the model.

The imitation model that we have written exhibits an interesting spatial pattern in the emergence of a dominant color. All of the agents coordinate locally. The coordinating neighborhoods spread until one neighborhood dominates the others. This kind of spatial pattern is also observed in the best reply and reproduction models. And, it is often a very good approximation of natural behavior. However, the underlying phenomenon in these models is the spatially constrained networks of interacting agents. When these networks are characterized by local neighborhoods, they exhibit spatially localized behavior patterns. However, networks of interactions can take many forms, and exhibit many kinds of patterns.

If, for example, we wanted to change the network structure of the best reply model so that agents were not playing their local neighbors, but rather could play any random agent in the model, we would only have to change one line of code. Instead of the PLAY_RANDOM_NEIGHBOR rule, we could use the PLAY_OTHER rule. This rule tells the agent to execute the play() method with some random agent in the scape. Essentially, this change of rule turns a local interaction model into a global interaction model. The end result is the same, however the spatial pattern in the model is lost, and the model takes longer to converge. So, in this case the agent has a much more disperse, by still dynamic, network. Except in very abstract models, this network structure is generally undesirable because its behavioral analog is that agents can interact randomly with any member of the entire population at any time. This seems, in most cases, unlikely if not implausible.

A different, more plausible, social network structure is a network that is neither dynamic nor spatial. In such a network, we begin by assigning each agent a collection of agents that constitute its social network. These agents, however, are not the spatially related to one another. They can be randomly assigned, or assigned based on some other property (say, membership in a club or society). The point is that these agents interact with one another as part of a social network, even though they are not spatially related to one another. This kind of network highlights the fact that what is essential about the models that we have been looking at is how the network of agents is constituted. Spatial factors are often the most salient in the construction of dynamic social networks. However, networks of interacting agents will often be dispersed within a population. Further, agents will often have multiple sets of social networks for different kinds of interactions.

Using the basic coordination model as a starting point, we can construct an example of this new kind of social network model. It is one in which as agents move around, they keep a small, static network of 'friends' agents against whom they judge their success. They use this network to evaluate their strategies, and determine what color to adopt. At the same time, they play the coordination game in local neighborhoods. So, the local social networks determine the agents' payoffs, while the static friends networks determine their behavior (color choice). While a well-scoring agent will dominate the strategies in a friends network, this dominance does not affect the choices of his game-playing network. Consequently, the reinforcement mechanism found in the original imitation model is not present, so neighborhoods do not show the same patterns of spatial coordination as in the earlier models. However, global coordination in the model is achieved more quickly precisely because there are no 'neighborhood effects', where pockets of reinforcement allow a minority population to keep imitating one another. The diffusiveness of social influence in this social network model allows the population to coordinate much more quickly, and dramatically.

Friends Network Model

To write this model, we begin by having each agent select four random agents to be part of its friends network. Once these agents are selected, they will always be the four agents that the agent uses to evaluate its strategy. As the model runs, the agents migrate to new neighborhoods, and play different agents, but they always refer to their friends network when deciding what color to play. In the model we will write, friends networks are not symmetric, which is to say that if A has B in its friends network, there is no guarantee that B has A in its network. We can change this later to make the social networks more tight-nit, but it seems intuitively plausible at the outset that people might imitate friends or acquaintances who will not imitate them.

To make the imitation Coordination Game Model into a friends-network model, the first thing to change is the initial setup. We need to create the social network when the model is created. To do this, we will add a rule to the scape that tells each agent in the scape to pick four random agents and to create a social network of these agents. This rule, like the MOVE_RANDOM_LOCATION_RULE, will only be called when the model is initialized, and so will be added to the scape using the addInitialRule() method. However, there is no existing rule for setting up social networks, so we will have to create a new rule.

```
          public void scapeCreated() {
              getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
              getScape().addInitialRule(new Rule("SetNewNetwork")
              {
                          public void execute(Agent agent) {
     ((CoordinationGamePlayer) agent).setNewNetwork();
                          }
              });
              getScape().addRule(RANDOM_WALK_RULE);
              getScape().addRule(UPDATE_RULE);
             getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);
          }
```

I have called the new rule "SetNewNetwork". Creating a new rule simply involves creating an instance of the Rule class and writing an execute() method that takes an agent as an argument (overriding the existing execute() method in the Rule class) and tells the agent what to do. In this case, the execute() method simply tells the agent to call its setNewNetwork() method. Now, to create the social network, all we need to do is to create the setNewNetwork() method.

First, we add a few arrays to the CoordinationGamePlayer class.

```
     public class CoordinationGamePlayer extends CellOccupant   {
          protected Agent[] scapearray;
     protected CoordinationGamePlayer[] friends;
          .
          .
          .
     }
```

The first array will hold a list of all of the agents in the scape (so that we can pick our set of friends from this list). The second array will hold the list of friends. This 'friends' array will be given to the setNetwork() method to create the friends network. We can initialize the 'friends' array to any size, and that will determine the size of network. So that we can have runtime control over this variable, we will make a model variable 'friends_size', and will use that to initialize the 'friends' array.

```
     public class CoordinationGame extends Scape {
              public int friends_size = 4;
          .
          .
          .
     }

     public class CoordinationGamePlayer extends CellOccupant   {
          .
          .
          .
          public void initialize() {
               doRandom();
               recentPlays = new int [5];
```

```
                recentPartners = new Color [5];
        friends = new CoordinationGamePlayer [((Coord)getModel()).friends_size];
                }
                .
                .
                .
        }
```

Now, to actually create the friends network, we go back to the CoordinationGamePlayer class and add the setNewNetwork() method.

```
        public void setNewNetwork(){
                //populate the scapearray array
                scapearray = ((CoordinationGame)getModel()).players.getAgents
();
                for (int i = 0; i < network.length; i++){
                        findFriend(i);
                }
                //use the setNetwork call
                this.setNetwork(friends);
        }

        //find random friends, avoiding redundancy
        public void findFriend(int i){
                        int spot;
                        spot = randomInRange(0,(scapearray.length - 1));
                        if (scapearray[spot] == null)
                              {
                                      findFriend(i);
                              }
                        else
                              {
                              friends[i] = (CoordinationGamePlayer) scapearray
[spot];
                              scapearray[spot] = null;
                              }
        }
```

We first populate the scapearray with all of the agents in the 'players' scape. Then, we simply select random agents from the scapearray, and add them to the 'friends' array. We remove the agents from the scapearray once they have been selected (to eliminate the possibility of redundancy). When the 'friends' array is full, we call the setNetwork() method. The setNetwork() method simply keeps a record of the agents in the 'friends' array. The benefit of using the setNetwork() call, and its complimentary method that we use below, getNetwork(), is that they allow the developer to call setDrawGraph() from the 2D Lattice view. This call draws the network connections between agents on the screen, and allows the user to see which agents are part of which networks. Thus, using the get() and set() methods for networks simply adds a handy visualization functionality that wouldn't be available if we were to simply use the 'friends' array to keep track of our social network.

Once the network is created, actually changing the agents' behaviors so that they use a friends network to make their evaluations, instead of the local neighborhood, is very easy; it only involves changing two lines of code. We simply tell the update() method to iterate through the friends network instead of the local network when the agent is looking for someone to imitate. First, we comment out the original two lines of code where we create the array of 'neighbors' agents. Then, we add them back in, but this time the 'neighbors' array is an array of Cells (because that is how networks are stored by Ascape). Then we use the getNetwork() method to return the list of friends in our network (which we will cast to CoordinationGamePlayer agents when we iterate through the list).

```
public void update() {
        count++;
        if (count > recentPlays.length)
        {

                if (randomInRange(0,100) >= ((CoordinationGame)getModel
()).error)
                {
                        int currScore = 0;
                        int bestScore = this.totalScore;
                        //CellOccupant[] neighbors;
                        //neighbors = getHostCell().getNeighboringOccupants
                ();

                        //New Social Network Code
                        Cell[] neighbors;
                        neighbors = getNetwork();
                        //End New Social Network Code
                           for (int i = 0; i < neighbors.length; i++)
                           {
                           currScore = ((CoordinationGamePlayer)neighbors
                        [i]).totalScore;
                                if (currScore > bestScore)
                                        {
                                        bestScore = currScore;
                                        myColor = ((CoordinationGamePlayer)
                                        neighbors[i]).getColor();
                                        }
                                }
                }
                else
                {
                        doRandom();
                }

        }

}
```

Below, are some images of the above network model running. Notice the mixing of strategies in the population and how quickly they converge.

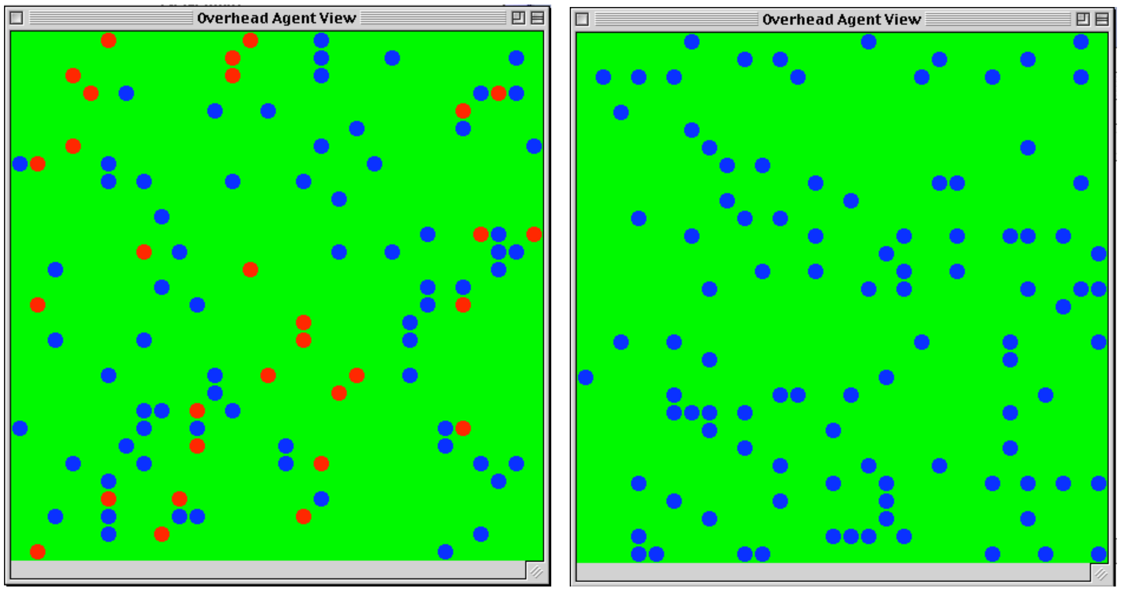


Fig.42: Social Networks Model at t = 14 and t = 30.

To add the social networks visualization to the model, we simply add the following line of code to the createGraphicViews() method in the CoordinationGame class.

```
public void createGraphicViews() {
                overheadView.setDrawNetwork(true);
}
```

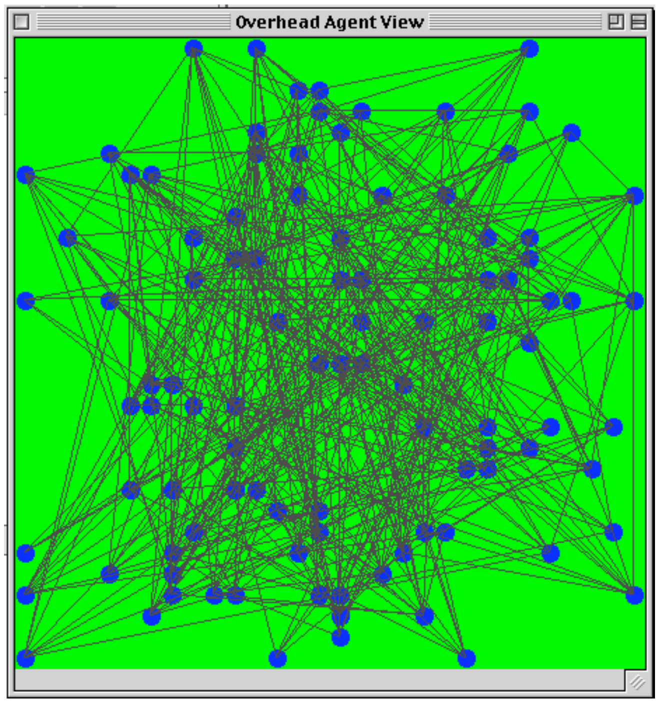


Fig.43: View showing social network ties

There are many interesting permutations of the above social networks model. We can change the interaction networks so that agents play the coordination game with their friends networks and imitate their local neighbors, or we can make the friendship (imitation) relations symmetric. Each of these changes can dramatically alter the dynamics of the model. The basic lesson from network models is that patterns of behavior diffuse much faster through disperse social networks but do not exhibit the discreet spatial patterns that are the hallmark of local interaction models.

In addition to the set() and get() calls for Networks, there are also set() and get() calls for local neighborhoods (setNeighbors() and getNeighbors()). Using these methods actually changes the topology of the lattice so as to make neighbors, in the local, von Neumann sense of neighborhoods, randomly distributed around the graph. In point of fact, setting the neighborhood for an agent and setting a network for an agent can be behaviorally equivalent. However, computationally, they are very different since the former allows an agent to use the Cell and Scape methods such as getNeighbors() and PLAY_RANDOM_NEIGHBOR, to interact with cells that are not spatially related to it. As in the friends network model, we can write analogous methods to perform these operations in a network, but the underlying machinery of the local neighborhoods is unchanged, so the Cell and Scape methods with still refer to the local neighborhood. Setting the Neighborhoods on a scape is tantamount to actually rearranging the geometry of the interactions. Setting a network simply ignores the neighborhood in favor of interacting with a different network of agents.

Summary and Conclusion

This concludes the Ascape tutorial. At this point you should be able to develop basic Ascape models, consulting the API documentation for information about how to use functionalities not covered in the tutorial. The basic point to keep in mind while developing in Ascape is that every scape controls the activation and behavior of its member agents. The members of the root scape are (at the very least) a 'players' scape and a scape graph. These two 'agents' are activated by the root scape's ITERATE rule. Then, each of these scapes activate their own agents with their own sets of rules. In some cases, the agents activated by the 'players' scape, or by some other scape, will be other scapes that hold different agents, and these agents will be told what to do directly by their parent scapes. Thus, collections of agents can interact as agents, and then tell their member agents to perform yet other rules. The possibilities are vast for developing models of societies, and of complex interacting agents.

Appendix. Code Samples

In order for these code samples to compile, the developer must have ascape and related libraries available on the classpath. Additionally, the files ‘CoordinationGame.java’ and ‘CoordinationGamePlayer.java’ should be in a src code directory that matches the package structure, i.e. [src]/edu.brook.manual.model[n]/.

Model 1: Coordination Game

CoordinationGame.java

```
package edu.brook.manual.model1;

import java.awt.Color;

import org.ascape.model.HostCell;
import org.ascape.model.Scape;
import org.ascape.model.event.ScapeEvent;
import org.ascape.model.space.Array2DVonNeumann;
import org.ascape.util.data.StatCollector;
import org.ascape.util.data.StatCollectorCond;
import org.ascape.view.vis.ChartView;
import org.ascape.view.vis.Overhead2DView;

public class CoordinationGame extends Scape {

    // model-scope variables
    protected int nPlayers = 100;

    protected int latticeWidth = 30;

    protected int latticeHeight = 30;

    public int coordinateOnBlue = 1;

    public int coordinateOnRed = 1;

    public int error = 0;

    Scape lattice;

    Scape players;

    Overhead2DView overheadView;

    // creates scapes and agents
    public void createScape() {
        super.createScape();
        lattice = new Scape(new Array2DVonNeumann());
        lattice.setPrototypeAgent(new HostCell());
        lattice.setExtent(latticeWidth, latticeHeight);

        CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
        cgplayer.setHostScape(lattice);
        players = new Scape();
        players.setName("Players");
        players.setPrototypeAgent(cgplayer);
        players.setExecutionOrder(Scape.RULE_ORDER);

        add(lattice);
        add(players);

        StatCollector CountReds = new StatCollectorCond("Reds") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).myColor ==
Color.red);
            }
        };
        StatCollector CountBlues = new StatCollectorCond("Blues") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).myColor ==
Color.blue);
            }
        };

        players.addStatCollector(CountReds);
        players.addStatCollector(CountBlues);
    }

    public void scapeSetup(ScapeEvent scapeEvent) {
        ((Scape) players).setExtent(nPlayers);
    }

 // create views and charts
     public void createGraphicViews() {
         super.createGraphicViews();
         ChartView chart = new ChartView();
         players.addView(chart);
         chart.addSeries("Count Reds", Color.red);
         chart.addSeries("Count Blues", Color.blue);
         chart.setDisplayPoints(100);

         overheadView = new Overhead2DView();
         overheadView.setCellSize(15);
         lattice.addView(overheadView);
     }

    // get() and set() methods for the model variables
    public int getRedScore() {
        return coordinateOnRed;
    }

    public void setRedScore(int NewcoordinateOnRed) {
        coordinateOnRed = NewcoordinateOnRed;
    }

    public int getBlueScore() {
        return coordinateOnBlue;
    }

    public void setBlueScore(int NewcoordinateOnBlue) {
        coordinateOnBlue = NewcoordinateOnBlue;

    }

    public int getnPlayers() {
        return nPlayers;
    }

    public void setnPlayers(int NewnPlayers) {
        nPlayers = NewnPlayers;

    }
}
}
```

CoordinationGamePlayer.java

```
package edu.brook.manual.model1;

import java.awt.Color;
import java.util.List;

import org.ascape.model.Agent;
import org.ascape.model.CellOccupant;

public class CoordinationGamePlayer extends CellOccupant {

// cgplayer variables
    protected Color myColor;

    protected int totalScore;

    protected int[] recentPlays;

    protected int count = 0;

    protected int totalreds;

    protected int totalblues;

// agent initialization method
    public void initialize() {
        if (randomInRange(0, 1) > 0) {
            myColor = Color.red;
        } else {
            myColor = Color.blue;
        }
        recentPlays = new int[5];
    }

// add rules to the scape
    public void scapeCreated() {
        getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
        getScape().addRule(RANDOM_WALK_RULE);
        getScape().addRule(UPDATE_RULE);
        getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);

    }

// imitation rule
    public void update() {
        count++;
        if (count > recentPlays.length) {
            int currScore = 0;
            int bestScore = this.totalScore;
            List neighbors = findNeighborsOnHost();
            for (Object neighbor : neighbors) {
                currScore = ((CoordinationGamePlayer) neighbor).totalScore;
                if (currScore > bestScore) {
                    bestScore = currScore;
                    myColor = ((CoordinationGamePlayer) neighbor).getColor();
                }
            }
        }
    }

    // play rule
    public void play(Agent partner) {
        int score;
        if (((((CoordinationGamePlayer) partner).getColor() == myColor) &&
(myColor == Color.blue)) {
            score = ((CoordinationGame) getRoot()).getBlueScore();
        } else if (((((CoordinationGamePlayer) partner).getColor() == myColor)
&& (myColor == Color.red)) {
            score = ((CoordinationGame) getRoot()).getRedScore();
        } else {
            score = 0;
        }
        count = count + 1;
        updateRecentPlays(score);
    }

    // keep track of the recent scores
    public void updateRecentPlays(int score) {
        totalScore = 0;
        for (int i = 0; i < (recentPlays.length - 1); i++) {
            recentPlays[i] = recentPlays[i + 1];
            totalScore = totalScore + recentPlays[i];
        }
        recentPlays[recentPlays.length - 1] = score;
        totalScore = totalScore + recentPlays[recentPlays.length - 1];
    }

    // cgplayer get() and set() methods
    public Color getColor() {
        return myColor;
    }

    public void setColor(Color ncolor) {
        myColor = ncolor;
    }
}
```

Model 2: Stochasticity and Averaging Statistics

CoordinationGame.java

```
package edu.brook.manual.model2;

import java.awt.Color;

import org.ascape.model.HostCell;
import org.ascape.model.Scape;
import org.ascape.model.event.ScapeEvent;
import org.ascape.model.space.Array2DVonNeumann;
import org.ascape.util.data.StatCollector;
import org.ascape.util.data.StatCollectorCSAMM;
import org.ascape.util.data.StatCollectorCond;
import org.ascape.view.vis.ChartView;
import org.ascape.view.vis.Overhead2DView;

public class CoordinationGame extends Scape {

    // model-scope variables
    protected int nPlayers = 100;

    protected int latticeWidth = 30;

    protected int latticeHeight = 30;

    public int coordinateOnBlue = 1;

    public int coordinateOnRed = 1;

    public int error = 0;

    Scape lattice;

    Scape players;

    Overhead2DView overheadView;

    // creates scapes and agents
    public void createScape() {
        super.createScape();
        lattice = new Scape(new Array2DVonNeumann());
        lattice.setPrototypeAgent(new HostCell());
        lattice.setExtent(latticeWidth, latticeHeight);

        CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
        cgplayer.setHostScape(lattice);
        players = new Scape();
        players.setName("Players");
        players.setPrototypeAgent(cgplayer);
        players.setExecutionOrder(Scape.RULE_ORDER);
        add(lattice);
        add(players);

        StatCollector CountReds = new StatCollectorCond("Reds") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.red);
            }
        };
        StatCollector CountBlues = new StatCollectorCond("Blues") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor()==
Color.blue);
            }
        };
        StatCollector AvgPayoff = new StatCollectorCSAMM("Payoff") {
            public double getValue(Object object) {
                return ((CoordinationGamePlayer) object).getRunningTotal();
            }
        };

        players.addStatCollector(CountReds);
        players.addStatCollector(CountBlues);
        players.addStatCollector(AvgPayoff);
    }

    public void scapeSetup(ScapeEvent scapeEvent) {
        ((Scape) players).setExtent(nPlayers);
    }

    // create views and charts
    public void createGraphicViews() {
        super.createGraphicViews();
        ChartView chart = new ChartView();
        players.addView(chart);
        chart.addSeries("Count Reds", Color.red);
        chart.addSeries("Count Blues", Color.blue);
        chart.addSeries("Average Payoff", Color.black);
        chart.setDisplayPoints(100);

        overheadView = new Overhead2DView();
        overheadView.setCellSize(15);
        lattice.addView(overheadView);
    }

    // get() and set() methods for the model variables
    public int getRedScore() {
        return coordinateOnRed;
    }

    public void setRedScore(int NewcoordinateOnRed) {
        coordinateOnRed = NewcoordinateOnRed;

    }
    public int getBlueScore() {
        return coordinateOnBlue;
    }

    public void setBlueScore(int NewcoordinateOnBlue) {
        coordinateOnBlue = NewcoordinateOnBlue;

    }

    public int getError() {
        return error;
    }

    public void setError(int NewError) {
        error = NewError;
    }

    public int getnPlayers() {
        return nPlayers;
    }

    public void setnPlayers(int NewnPlayers) {
        nPlayers = NewnPlayers;

    }
}
```

CoordinationGamePlayer.java

```
package edu.brook.manual.model2;

import java.awt.Color;
import java.util.List;

import org.ascape.model.Agent;
import org.ascape.model.CellOccupant;

public class CoordinationGamePlayer extends CellOccupant {

// cgplayer variables
    protected Color myColor;

    protected int totalScore;

    protected int[] recentPlays;

    protected int count = 0;

    protected int totalreds;

    protected int totalblues;

// agent initialization method
```

```
    public void initialize() {
        if (randomInRange(0, 1) > 0) {
            myColor = Color.red;
        } else {
            myColor = Color.blue;
        }
        recentPlays = new int[5];
    }

// add rules to the scape
    public void scapeCreated() {
        getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
        getScape().addRule(RANDOM_WALK_RULE);
        getScape().addRule(UPDATE_RULE);
        getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);

    }

// imitation rule
    public void update() {
        count++;
        if (count > recentPlays.length) {

            if (randomInRange(0, 100) >= ((CoordinationGame) getRoot()).error)
{
                int currScore = 0;
                int bestScore = this.totalScore;
                List neighbors = findNeighborsOnHost();
                for (Object neighbor : neighbors) {
                    currScore = ((CoordinationGamePlayer) neighbor).totalScore;
                    if (currScore > bestScore) {
                        bestScore = currScore;
                        myColor = ((CoordinationGamePlayer) neighbor).getColor
();
                    }
                }
            } else {
                if (randomInRange(0, 1) > 0) {
                    myColor = Color.red;
                } else {
                    myColor = Color.blue;
                }
            }
        }
    }

    // play rule
    public void play(Agent partner) {
        int score;
        if ((((CoordinationGamePlayer) partner).getColor() == myColor) &&
(myColor == Color.blue)) {
            score = ((CoordinationGame) getRoot()).getBlueScore();
        } else if ((((CoordinationGamePlayer) partner).getColor() == myColor)
&& (myColor == Color.red)) {
```

```
            score = ((CoordinationGame) getRoot()).getRedScore();
        } else {
            score = 0;
        }
        count = count + 1;
        updateRecentPlays(score);
    }

    // keep track of the recent scores
    public void updateRecentPlays(int score) {
        totalScore = 0;
        for (int i = 0; i < (recentPlays.length - 1); i++) {
            recentPlays[i] = recentPlays[i + 1];
            totalScore = totalScore + recentPlays[i];
        }
        recentPlays[recentPlays.length - 1] = score;
        totalScore = totalScore + recentPlays[recentPlays.length - 1];
    }

    // cgplayer get() and set() methods
    public Color getColor() {
        return myColor;
    }

    public void setColor(Color ncolor) {
        myColor = ncolor;
    }

    public int getRunningTotal() {
        return (totalScore * 10);
    }

}
```

Model 3: Best Reply Dynamics

CoordinationGame.java

```
package edu.brook.manual.model3;

import java.awt.Color;

import org.ascape.model.HostCell;
import org.ascape.model.Scape;
import org.ascape.model.event.ScapeEvent;
import org.ascape.model.space.Array2DVonNeumann;
import org.ascape.util.data.StatCollector;
import org.ascape.util.data.StatCollectorCSAMM;
import org.ascape.util.data.StatCollectorCond;
import org.ascape.view.vis.ChartView;
import org.ascape.view.vis.Overhead2DView;

public class CoordinationGame extends Scape {

    // model-scope variables
    // model-scope variables
    protected int nPlayers = 100;

    protected int latticeWidth = 30;

    protected int latticeHeight = 30;

    public int coordinateOnBlue = 1;

    public int coordinateOnRed = 1;

    public int error = 0;

    Scape lattice;

    Scape players;

    Overhead2DView overheadView;

    // creates scapes and agents
    public void createScape() {
        super.createScape();
        lattice = new Scape(new Array2DVonNeumann());
        lattice.setPrototypeAgent(new HostCell());
        lattice.setExtent(latticeWidth, latticeHeight);

        CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
        cgplayer.setHostScape(lattice);
        players = new Scape();
        players.setName("Players");
        players.setPrototypeAgent(cgplayer);
        players.setExecutionOrder(Scape.RULE_ORDER);

        add(lattice);
        add(players);

        StatCollector CountReds = new StatCollectorCond("Reds") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.red);
            }
        };
        StatCollector CountBlues = new StatCollectorCond("Blues") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.blue);
            }
        };
        StatCollector AvgPayoff = new StatCollectorCSAMM("Payoff") {
            public double getValue(Object object) {
                return ((CoordinationGamePlayer) object).getRunningTotal();
            }
        };

        players.addStatCollector(CountReds);
        players.addStatCollector(CountBlues);
        players.addStatCollector(AvgPayoff);
    }

    public void scapeSetup(ScapeEvent scapeEvent) {
        ((Scape) players).setExtent(nPlayers);
    }

    // create views and charts
    public void createGraphicViews() {
        super.createGraphicViews();
        ChartView chart = new ChartView();
        players.addView(chart);
        chart.addSeries("Count Reds", Color.red);
        chart.addSeries("Count Blues", Color.blue);
        chart.addSeries("Average Payoff", Color.black);
        chart.setDisplayPoints(100);

        overheadView = new Overhead2DView();
        overheadView.setCellSize(15);
        lattice.addView(overheadView);
    }

    // get() and set() methods for the model variables
    public int getRedScore() {
        return coordinateOnRed;
    }

    public void setRedScore(int NewcoordinateOnRed) {
        coordinateOnRed = NewcoordinateOnRed;
    }

    public int getBlueScore() {
        return coordinateOnBlue;
    }

    public void setBlueScore(int NewcoordinateOnBlue) {
        coordinateOnBlue = NewcoordinateOnBlue;

    }

    public int getError() {
        return error;
    }

    public void setError(int NewError) {
        error = NewError;
    }

    public int getnPlayers() {
        return nPlayers;
    }

    public void setnPlayers(int NewnPlayers) {
        nPlayers = NewnPlayers;

    }
}
```

CoordinationGamePlayer.java

```
package edu.brook.manual.model3;

import java.awt.Color;

import org.ascape.model.Agent;
import org.ascape.model.CellOccupant;

public class CoordinationGamePlayer extends CellOccupant {

// cgplayer variables
    protected Color myColor;

    protected int totalScore;

    protected int[] recentPlays;

    protected Color[] recentPartners;

    protected int count = 0;

    protected int totalreds;
    protected int totalblues;

// agent initialization method
    public void initialize() {
        doRandom();
        recentPlays = new int[5];
        recentPartners = new Color [5];
    }

// add rules to the scape
    public void scapeCreated() {
        getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
        getScape().addRule(RANDOM_WALK_RULE);
        getScape().addRule(UPDATE_RULE);
        getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);

    }

    // best reply rule
    public void update() {
        count++;
        if (count > recentPlays.length) {

            if (randomInRange(0, 100) >= ((CoordinationGame) getRoot()).error)
{
                int redScore;
                int blueScore;
                blueScore = totalblues * ((CoordinationGame) getRoot
()).getBlueScore();

                redScore = totalreds * ((CoordinationGame) getRoot
()).getRedScore();
                if (redScore > blueScore) {
                    myColor = Color.red;
                } else if (blueScore > redScore) {
                    myColor = Color.blue;
                } else {
                    doRandom();
                }

            } else {
                doRandom();
            }
        }
    }

    public void doRandom() {
        if (randomInRange(0, 1) > 0) {
            myColor = Color.red;
        } else {
            myColor = Color.blue;
        }
    }
    // play rule
    public void play(Agent partner) {
        int score;
        if ((((CoordinationGamePlayer) partner).getColor() == myColor) &&
(myColor == Color.blue)) {
            score = ((CoordinationGame) getRoot()).getBlueScore();
        } else if ((((CoordinationGamePlayer) partner).getColor() == myColor)
&& (myColor == Color.red)) {
            score = ((CoordinationGame) getRoot()).getRedScore();
        } else {
            score = 0;
        }
        count = count + 1;
        updateRecentPlays(score);
        updateRecentPartners(((CoordinationGamePlayer) partner).getColor());
    }

    // keep track of recent partners
    public void updateRecentPartners(Color ncolor) {
        totalreds = 0;
        totalblues = 0;
        for (int i = 0; i < (recentPartners.length - 1); i++) {
            recentPartners[i] = recentPartners[i + 1];
            if (recentPartners[i] == Color.red) {
                totalreds = totalreds + 1;
            } else if (recentPartners[i] == Color.blue) {
                totalblues = totalblues + 1;
            }
        }
        recentPartners[recentPartners.length - 1] = ncolor;
        if (ncolor == Color.red) {
            totalreds = totalreds + 1;
        }
        if (ncolor == Color.blue) {
            totalblues = totalblues + 1;
        }
    }

    // keep track of the recent scores
    public void updateRecentPlays(int score) {
        totalScore = 0;
        for (int i = 0; i < (recentPlays.length - 1); i++) {
            recentPlays[i] = recentPlays[i + 1];
            totalScore = totalScore + recentPlays[i];
        }
        recentPlays[recentPlays.length - 1] = score;
        totalScore = totalScore + recentPlays[recentPlays.length - 1];
    }

    // cgplayer get() and set() methods
    public Color getColor() {
        return myColor;
    }
    public void setColor(Color ncolor) {
        myColor = ncolor;
    }

    public int getRunningTotal() {
        return (totalScore * 10);
    }
}
```

Model 4: Biological Coordination Game

CoordinationGame.java

```
package edu.brook.manual.model4;

import java.awt.Color;

import org.ascape.model.HostCell;
import org.ascape.model.Scape;
import org.ascape.model.event.ScapeEvent;
import org.ascape.model.space.Array2DVonNeumann;
import org.ascape.util.data.StatCollector;
import org.ascape.util.data.StatCollectorCSAMM;
import org.ascape.util.data.StatCollectorCond;
import org.ascape.view.vis.ChartView;
import org.ascape.view.vis.Overhead2DView;

public class CoordinationGame extends Scape {

    // model-scope variables
    // model-scope variables
    protected int nPlayers = 100;

    protected int latticeWidth = 30;

    protected int latticeHeight = 30;

    public int coordinateOnBlue = 1;

    public int coordinateOnRed = 1;

    public int error = 0;

    public int turns = 5;

    public int repScore = 5;

    public int minScore = 3;

    Scape lattice;

    Scape players;

    Overhead2DView overheadView;

    // creates scapes and agents
    public void createScape() {
        super.createScape();
        lattice = new Scape(new Array2DVonNeumann());
        lattice.setPrototypeAgent(new HostCell());
        lattice.setExtent(latticeWidth, latticeHeight);
        CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
        cgplayer.setHostScape(lattice);
        players = new Scape();
        players.setName("Players");
        players.setPrototypeAgent(cgplayer);
        players.setExecutionOrder(Scape.RULE_ORDER);

        add(lattice);
        add(players);

        StatCollector CountReds = new StatCollectorCond("Reds") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.red);
            }
        };
        StatCollector CountBlues = new StatCollectorCond("Blues") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.blue);
            }
        };
        StatCollector AvgPayoff = new StatCollectorCSAMM("Payoff") {
            public double getValue(Object object) {
                return ((CoordinationGamePlayer) object).getRunningTotal();
            }
        };

        players.addStatCollector(CountReds);
        players.addStatCollector(CountBlues);
        players.addStatCollector(AvgPayoff);
    }

    public void scapeSetup(ScapeEvent scapeEvent) {
        ((Scape) players).setExtent(nPlayers);
    }

    // create views and charts
    public void createGraphicViews() {
        super.createGraphicViews();
        ChartView chart = new ChartView();
        players.addView(chart);
        chart.addSeries("Count Reds", Color.red);
        chart.addSeries("Count Blues", Color.blue);
        chart.addSeries("Average Payoff", Color.black);
        chart.setDisplayPoints(100);

        overheadView = new Overhead2DView();
        overheadView.setCellSize(15);
        lattice.addView(overheadView);
    }

    // get() and set() methods for the model variables
    public int getRedScore() {
        return coordinateOnRed;
    }

    public void setRedScore(int NewcoordinateOnRed) {
        coordinateOnRed = NewcoordinateOnRed;

    }

    public int getBlueScore() {
        return coordinateOnBlue;
    }

    public void setBlueScore(int NewcoordinateOnBlue) {
        coordinateOnBlue = NewcoordinateOnBlue;

    }

    public int getError() {
        return error;
    }

    public void setError(int NewError) {
        error = NewError;
    }

    public int getnPlayers() {
        return nPlayers;
    }

    public void setnPlayers(int NewnPlayers) {
        nPlayers = NewnPlayers;
    }

    public int getTurnstoDie() {
        return turns;
    }

    public void setTurnstoDie(int Newnum) {
        turns = Newnum;

    }

    public int getrepScore() {
        return repScore;
    }

    public void setrepScore(int Newscore) {
        repScore = Newscore;

    }

    public int getMinDieScore() {
        return minScore;
    }
    public void setMinDieScore(int Newscore) {
        minScore = Newscore;

    }

}
```

CoordinationGamePlayer.java

```
package edu.brook.manual.model4;

import java.awt.Color;

import org.ascape.model.Agent;
import org.ascape.model.CellOccupant;

public class CoordinationGamePlayer extends CellOccupant {

// cgplayer variables
    protected Color myColor;

    protected int totalScore;

    protected int[] recentPlays;

    protected int count = 0;

    protected int totalreds;

    protected int totalblues;

// agent initialization method
    public void initialize() {
        doRandom();
        recentPlays = new int[5];
    }

// add rules to the scape
    public void scapeCreated() {
        getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
        getScape().addRule(RANDOM_WALK_RULE);
        getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);
        getScape().addRule(METABOLISM_RULE);
    }

    public void doRandom() {
        if (randomInRange(0, 1) > 0) {
            myColor = Color.red;
        } else {
            myColor = Color.blue;
        }
    }
    // play rule
    public void play(Agent partner) {
        int score;
        if ((((CoordinationGamePlayer) partner).getColor() == myColor) &&
(myColor == Color.blue)) {
            score = ((CoordinationGame) getRoot()).getBlueScore();
        } else if ((((CoordinationGamePlayer) partner).getColor() == myColor)
&& (myColor == Color.red)) {
            score = ((CoordinationGame) getRoot()).getRedScore();
        } else {
            score = 0;
        }
        count = count + 1;
        updateRecentPlays(score);
    }

    // keep track of the recent scores
    public void updateRecentPlays(int score) {
        totalScore = 0;
        for (int i = 0; i < (recentPlays.length - 1); i++) {
            recentPlays[i] = recentPlays[i + 1];
            totalScore = totalScore + recentPlays[i];
        }
        recentPlays[recentPlays.length - 1] = score;
        totalScore = totalScore + recentPlays[recentPlays.length - 1];
    }

    // either die or reproduce
    public void metabolism() {
        if (totalScore == ((CoordinationGame) getRoot()).getrepScore()) {
            count = 0;
            reproduce();
            for (int i = 0; i < (recentPlays.length - 1); i++) {

                recentPlays[i] = 0;
            }
        } else if (totalScore <= ((CoordinationGame) getRoot()).getMinDieScore
() && count >= ((CoordinationGame) getRoot()).getTurnstoDie()) {
            this.die();
        }
    }

    public void reproduce() {
        if (this.getHostCell().isNeighborAvailable()) {
            CoordinationGamePlayer baby = (CoordinationGamePlayer) this.clone
();
            getScape().add(baby);
            baby.initialize();
            baby.setColor(myColor);
            baby.moveTo(this.getHostCell().findRandomAvailableNeighbor());
        }
    }

    // cgplayer get() and set() methods
    public Color getColor() {
        return myColor;
    }

    public void setColor(Color ncolor) {
        myColor = ncolor;
    }

    public int getRunningTotal() {
        return (totalScore * 10);
    }

}
```

Model 5: Friends Network Model

CoordinationGame.java

```
package edu.brook.manual.model5;

import java.awt.Color;

import org.ascape.model.HostCell;
import org.ascape.model.Scape;
import org.ascape.model.event.ScapeEvent;
import org.ascape.model.space.Array2DVonNeumann;
import org.ascape.util.data.StatCollector;
import org.ascape.util.data.StatCollectorCSAMM;
import org.ascape.util.data.StatCollectorCond;
import org.ascape.view.vis.ChartView;
import org.ascape.view.vis.Overhead2DView;

public class CoordinationGame extends Scape {

    // model-scope variables
    // model-scope variables
    protected int nPlayers = 100;

    protected int latticeWidth = 30;

    protected int latticeHeight = 30;

    public int coordinateOnBlue = 1;

    public int coordinateOnRed = 1;

    public int error = 0;

    public int turns = 5;

    public int repScore = 5;

    public int minScore = 3;

    public int friends_size = 4;

    Scape lattice;

    Scape players;

    Overhead2DView overheadView;

    // creates scapes and agents
    public void createScape() {
        super.createScape();
        lattice = new Scape(new Array2DVonNeumann());
        lattice.setPrototypeAgent(new HostCell());
        lattice.setExtent(latticeWidth, latticeHeight);

        CoordinationGamePlayer cgplayer = new CoordinationGamePlayer();
        cgplayer.setHostScape(lattice);
        players = new Scape();
        players.setName("Players");
        players.setPrototypeAgent(cgplayer);
        players.setExecutionOrder(Scape.RULE_ORDER);

        add(lattice);
        add(players);

        StatCollector CountReds = new StatCollectorCond("Reds") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.red);
            }
        };
        StatCollector CountBlues = new StatCollectorCond("Blues") {
            public boolean meetsCondition(Object object) {
                return (((CoordinationGamePlayer) object).getColor() ==
Color.blue);
            }
        };
        StatCollector AvgPayoff = new StatCollectorCSAMM("Payoff") {
            public double getValue(Object object) {
                return ((CoordinationGamePlayer) object).getRunningTotal();
            }
        };

        players.addStatCollector(CountReds);
        players.addStatCollector(CountBlues);
        players.addStatCollector(AvgPayoff);
    }

    public void scapeSetup(ScapeEvent scapeEvent) {
        ((Scape) players).setExtent(nPlayers);
    }

    // create views and charts
    public void createGraphicViews() {
        super.createGraphicViews();
        ChartView chart = new ChartView();
        players.addView(chart);
        chart.addSeries("Count Reds", Color.red);
        chart.addSeries("Count Blues", Color.blue);
        chart.addSeries("Average Payoff", Color.black);
        chart.setDisplayPoints(100);

        overheadView = new Overhead2DView();
        overheadView.setCellSize(15);
        overheadView.setDrawNetwork(true);
        lattice.addView(overheadView);
    }

    // get() and set() methods for the model variables
    public int getRedScore() {
        return coordinateOnRed;
    }

    public void setRedScore(int NewcoordinateOnRed) {
        coordinateOnRed = NewcoordinateOnRed;

    }

    public int getBlueScore() {
        return coordinateOnBlue;
    }

    public void setBlueScore(int NewcoordinateOnBlue) {
        coordinateOnBlue = NewcoordinateOnBlue;

    }

    public int getError() {
        return error;
    }

    public void setError(int NewError) {
        error = NewError;
    }

    public int getnPlayers() {
        return nPlayers;
    }

    public void setnPlayers(int NewnPlayers) {
        nPlayers = NewnPlayers;
    }

    public int getTurnstoDie() {
        return turns;
    }

    public void setTurnstoDie(int Newnum) {
        turns = Newnum;

    }

    public int getrepScore() {
        return repScore;
    }

    public void setrepScore(int Newscore) {
        repScore = Newscore;

    }
    public int getMinDieScore() {
        return minScore;
    }

    public void setMinDieScore(int Newscore) {
        minScore = Newscore;

    }

    public Scape getPlayers() {
        return players;
    }
}
```

CoordinationGamePlayer.java

```
package edu.brook.manual.model5;

import java.awt.Color;
import java.util.ArrayList;
import java.util.List;

import org.ascape.model.Agent;
import org.ascape.model.CellOccupant;
import org.ascape.model.rule.Rule;

public class CoordinationGamePlayer extends CellOccupant {

// cgplayer variables
    protected Color myColor;

    protected int totalScore;

    protected int[] recentPlays;

    protected int count = 0;

    protected int totalreds;

    protected int totalblues;

    protected List<CoordinationGamePlayer> friends;

// agent initialization method
    public void initialize() {
        doRandom();
        recentPlays = new int[5];
        friends = new ArrayList<CoordinationGamePlayer>();

    }
```

```
// add rules to the scape
    public void scapeCreated() {
        getScape().addInitialRule(MOVE_RANDOM_LOCATION_RULE);
        getScape().addInitialRule(new Rule("SetNewNetwork") {
            public void execute(Agent agent) {
                ((CoordinationGamePlayer) agent).setNewNetwork();
            }
        });
        getScape().addRule(RANDOM_WALK_RULE);
        getScape().addRule(UPDATE_RULE);
        getScape().addRule(PLAY_RANDOM_NEIGHBOR_RULE);
    }

    public void doRandom() {
        if (randomInRange(0, 1) > 0) {
            myColor = Color.red;
        } else {
            myColor = Color.blue;
        }
    }

    // imitation rule
    public void update() {
        count++;
        if (count > recentPlays.length) {

            if (randomInRange(0, 100) >= ((CoordinationGame) getRoot()).error)
{
                int currScore = 0;
                int bestScore = this.totalScore;
                // CellOccupant[] neighbors;
                // neighbors = getHostCell().getNeighboringOccupants();
                // New Social Network Code
                List neighbors = getNetwork();
                for (Object agent : neighbors) {
                    currScore = ((CoordinationGamePlayer) agent).totalScore;
                    if (currScore > bestScore) {
                        bestScore = currScore;
                        myColor = ((CoordinationGamePlayer) agent).getColor();
                    }
                }
            } else {
                doRandom();
            }

        }
    }

    // play rule
    public void play(Agent partner) {
        int score;
        if ((((CoordinationGamePlayer) partner).getColor() == myColor) &&
(myColor == Color.blue)) {
            score = ((CoordinationGame) getRoot()).getBlueScore();
        } else if ((((CoordinationGamePlayer) partner).getColor() == myColor)
&& (myColor == Color.red)) {
            score = ((CoordinationGame) getRoot()).getRedScore();
        } else {
            score = 0;
        }
        count = count + 1;
        updateRecentPlays(score);
    }

    // keep track of the recent scores
    public void updateRecentPlays(int score) {
        totalScore = 0;
        for (int i = 0; i < (recentPlays.length - 1); i++) {
            recentPlays[i] = recentPlays[i + 1];
            totalScore = totalScore + recentPlays[i];
        }
        recentPlays[recentPlays.length - 1] = score;
        totalScore = totalScore + recentPlays[recentPlays.length - 1];
    }

    // create friends networks at model setup
    public void setNewNetwork() {
        friends.clear();
        for (int i = 0; i < ((CoordinationGame) getRoot()).friends_size; i++) {
            friends.add((CoordinationGamePlayer) ((CoordinationGame) getRoot
()).getPlayers().findRandom());
        }
        this.setNetwork(friends);
    }

    // cgplayer get() and set() methods
    public Color getColor() {
        return myColor;
    }

    public void setColor(Color ncolor) {
        myColor = ncolor;
    }

    public int getRunningTotal() {
        return (totalScore * 10);
    }

}
```