Chapter 8

Complex Adaptive Social Systems in One Dimension

Be patient, for the world is broad and wide.
Edwin A. Abbott, *Flatland*

We begin with a set of very simple models designed to illuminate some basic issues inherent in complex adaptive social systems. In Abbott's *Flatland*, geometric figures confined to living in a two-dimensional world gain insight into the third-dimension when a sphere slowly passes through their plane. The sphere begins as a point, grows into ever larger circles and eventually reverses its course and returns to a point, and disappears. After seeing this amazing sequence of activity, the figures confined to Flatland begin to glimpse the third dimension. Here we explore some simple models with a similar motivation to Abbott's sphere, namely to provide some useful glimpses into the behavior of complex adaptive social systems.

Modeling any system is often an exploratory process that requires both induction and deduction. You begin by making a simple set of assumptions and see where they lead. From this experience you attempt to create better models or deduce more exact results. The discussion below follows this approach. We begin with a rather stark notion of a social system of interacting agents and from this attempt to direct the analysis down productive paths. Our goal is not only to illustrate how such models can be developed and analyzed, but also to create a series of easily digestible models that embody many of the key concepts and insights that have been developed in complex adaptive social systems over the past decade. These devilishly simple models were not some random stroll through the set of possibilities, but contain a significant malice of forethought.

The agents in the models below populate a one-dimensional circular world—for concreteness, consider a world in which agents live atop a large atoll. Around this atoll we have N sites that can be occupied by the agents. For ease of exposition, we consecutively number these sites $1, 2, \ldots, N$ starting from an arbitrary point, and thus the Nth site completes the circle and abuts site 1. Given this world, we can impose a natural constraint on agent interactions, namely that agents interact within neighborhoods of contiguous sites. Thus, an agent at site 1 has a "right-hand" neighbor at site 2 and a "left-hand" neighbor at site N.[1]

In the initial models, agents must take one of two possible actions (designated by 0 and 1). Each agent chooses its action using a fixed behavioral rule. This behavioral rule depends only upon the most recently observed actions taken by the agent and its designated neighbors. While this construction is obviously very sparse, it is sufficient to demonstrate a number of the core features that arise in complex adaptive social systems and computational modeling.

A crucial difference between models of complex social and physical systems is in our assumptions about appropriate behavioral rules. Quantum effects aside, one hydrogen atom acts just like another hydrogen atom relying on a set of fixed, external physical properties and forces. Social agents, on the other hand, often alter their behavior in response to, and in anticipation of, the actions of others.[2] The atoms on the bumpers of two cars about to collide do not alter their behavior; the drivers of the two cars typically do, albeit a bit late. As a result, social systems have an additional layer of complication over physical ones, and we must make sure that the behavioral rules deployed by our agents make sense in this broader context. We will initially explore systems with simple fixed rules to gain some basic insights and intuitions. Eventually, we will introduce more complex rules that can "change" their behavior over time.

One can often think of complex adaptive systems as having micro-level agents (in the case of our atoll, "Micronesians") interacting to create the global properties of the system. These global properties then feedback into

[1] We can extend this idea to larger neighborhoods as well. An agent at site 1 has immediate neighbors at sites 2 and N, neighbors two-steps away at sites 3 and $N-1$, etc.

[2] As we discussed previously, even "adaptive" rules are fixed at the deepest levels.

the micro-level interactions in various ways. Such feedbacks occur in both physical systems, like earthquakes, and social ones, like stock market crashes. What differentiates physical systems from social ones, is that agents in social systems often alter their behavior in response to anticipated outcomes. Rocks on the boundaries of tectonic plates just let earthquakes happen; people, attempt to prevent stock market crashes.

8.1 Cellular Automata

The first model we explore is one in which each agent's behavior is driven by the same generic rule. Consider an atoll of size 20, where each site is occupied by an agent that has two possible actions $\{0, 1\}$. We assume that each agent's behavior is controlled by the *identical* rule, and that this rule uses the most recent action of the agent in question and its two nearest neighbors to determine the next action. Given that actions are binary, a fully specified rule will need to map the eight possible (2^3) combinations of actions that the agent and its two neighbors can take, into the agent's next action. Since the rule must designate a binary action (either 0 or 1) for each of the eight situations, there are 256 (2^8) possible rules that could direct an agent's behavior.

Table 8.1 shows the rule table for Rule 22.[3] A rule table is a mapping from each possible input state to an output state. The first line of this rule table (Situation 0) specifies that if an agent and its two neighbors all took action 0 last time, then the agent will want to take action 0. The next line (Situation 1) indicates that if the agent and its left neighbor took action 0 and the right neighbor took action 1, then the agent will want to take action 1, etc. In Table 8.2 we show the dynamics of this simple rule. The sites of the atoll are numbered from 1 to 20 moving left to right (recall that the left and right-hand edges of the table are connected to one another, so a more accurate representation would entail forming the table into a cylinder by rolling the outer edge of the page in toward the binding). At time 0, we randomly pick an action for each agent. At each subsequent iteration the agents simultaneously choose their next actions based on the rule in Table 8.1 and the actions observed in the previous time step.

[3] A standard way of referring to such rules is by using the integer equivalent of the bits that define the rule table. Thus, in Table 8.1 the defining bits of the rule table are 00010110 which can be interpreted as the integer value 22.

Situation	Left Neighbor	Self	Right Neighbor	Rule 22
0	0	0	0	0
1	0	0	1	1
2	0	1	0	1
3	0	1	1	0
4	1	0	0	1
5	1	0	1	0
6	1	1	0	0
7	1	1	1	0

Table 8.1: A simple behavioral rule.

Time Step	Actions
0	00111011100111001000
1	01000000011000111100
2	11100000100101000010
3	00010001111101100110
4	00111010000000001001
5	11000011000000100111
6	00100100100001111000
7	01111111110010000100
8	10000000001111001110
9	11000000010000110000
10	00100000111001001001
11	11110001000111111111
12	00001011101000000000
13	00011000001100000000
14	00100100010010000000
15	01111110111111000000

Table 8.2: Dynamics of Rule 22.

This simple rule results in some interesting system-wide behavior. As can be seen in Table 8.2, coherent macro structures in the form of downward facing triangles composed of 0's emerge throughout the diagram. The scale of these triangles goes well beyond the scale of the behavioral rules. Thus, even though individual behavior is based on the actions observed at three sites, coherent triangular structures emerge that encompass far more sites (for example, at time twelve a triangle forms across thirteen of the twenty sites). Like Smith's invisible hand, it is as if the actions of the agents are being coordinated to create patterns that are no part of any agent's intention.

While there is some coherence in the outcome, there is also perpetual novelty. Thus, while the system has a "theme" of a recurring series of downward facing triangles, their sizes and locations seem to vary across space and time in such a way that we never seem to see the exact pattern twice. This latter point needs to be qualified. Our system has only a finite number of possible states—with an atoll of size twenty, there are 2^{20} (a little over a million) possible unique configurations of the agents' actions. Since the rules are deterministic, any particular configuration is always followed by the same subsequent configuration. Therefore if we run the system long enough (at most 2^{20} time steps) it is guaranteed to hit the same configuration twice, and once this happens it will begin a cycle that follows the same path as it did when it first hit the repeated configuration. All finite, deterministic systems are guaranteed to cycle, though the lengths of these cycles can be relatively long.

The above rule demonstrates how simple, local interactions among agents can result in interesting aggregate behavior. The rule above is just one of 256 possible rules, and an obvious question is whether the behavior we see in this rule is in some sense generic. The answer is no. For example, a rule table where each possible situation results in a 1 will immediately lock the system into an equilibrium where all agents do action 1 after the first time step. Alternatively, a rule that always has an agent doing the opposite of what it did last period (that is, having 0's in situations 2, 3, 6, and 7, and 1's elsewhere) will cause the system to alternate back and forth with each time step.

Wolfram (1984, 2001) has systematically analyzed the 256 possible rules, and divided their behavior into four classes. Class 1 rules quickly evolve to a unique, homogeneous state with identical actions across the agents (as in the "all 1's" rule above). Class 2 rules result in separated groups of simple stable or periodic structures (as in the "do the opposite" rule). Class 3 rules imply chaotic patterns (the rule in Table 8.1 is a member of this class). Class 4 rules produce complex structures with long transients (patterns that can persist across space and time for extended periods) that are hypothesized to be capable of universal computation, that is, able to compute anything that can in principle be computed (Rule 110 meets this criterion).[4] One way to quantify the above classes is to measure how a random alteration of an action alters the behavior of the system in subsequent time periods. In Class 1 and 2 rules, such impacts are minimal, while in Classes 3 and 4 such disturbances can propagate across vast distances.

Wolfram's classification scheme allows us to abstract away particular details of the rules and still make good predictions about aggregate behavior. There are, however, problems with his classification scheme. In particular, the outcome of any given rule depends both on its structure and the initial conditions. It is possible for the behavior of a single rule to fall into two different classes. For example, in Table 8.3 we show the behavior of a rule that copies whatever the left neighbor did last period, under two different starting conditions. The initial conditions in World 1 lead to Class 1 behavior, while those in World 2 place the rule within Class 2. Rules can also start out in one class (by, say, displaying a very long transient) and then fall into a different class (by, perhaps, converging on to a low-period limit cycle). Notwithstanding these difficulties, Wolfram's attempts at classification represents an important step in creating more general theories of complex systems.

8.2 Social Cellular Automata

So far, we have demonstrated how simple systems of interacting agents modeled by cellular automata can result in interesting behavior. To convert these automata systems into models of social systems, we need some additional qualifications.

The first qualification is that we are willing to accept the notion that all agents employ a common, fixed rule. Many models of social systems embody such behavior by assuming a single, "representative" agent. Even when multiple rules across agents are possible, homogeneity can still arise through a variety of processes. For example, if all agents optimize the same problem in

[4]Analogs to continuous dynamic systems exist for the first three classes. Respectively, these are limit points, limit cycles, and chaotic attractors.