

Chapter XX

Relationships Between the Processes of Emergence and Abstraction in Societies

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ABSTRACT

This chapter presents an argument that the process of emergence is the converse of the process of abstraction. Emergence involves complex behavior resulting from simple rules, while abstraction forming simple rules that describe complex behavior. This converse relationship suggests the possibility that similar mechanisms underlie both processes, and a greater understanding of one can lead to a greater understanding of the other. Especially in the case of human and artificial social systems, the processes of abstraction and emergence are inextricably interconnected; the abstractions that individuals make will determine what behaviors emerge, and the behaviors that emerge in the society determine what abstractions will be made. This relationship between the two processes, which we call the abstraction-emergence loop, can be used to gain a better understanding of both. It is argued that the abstraction-emergence loop functions over various degrees of complexity and levels of detail, and that the loop has the greatest efficacy in certain ranges of detail. This way of understanding the two processes has particular bearing on social interactions; in order to understand macro-level emergent social phenomena, we must also simultaneously understand the micro-level phenomena from which they arise. In considering when emergence occurs, the role of the observer in the emergence abstraction loop is also discussed. In addition to describing various properties of the abstraction-emergence loop, this chapter presents descriptions of several ongoing and future research projects in the creation of autonomous agent societies, and offers pointers to future research directions aimed at exploring and understanding the nature of the abstraction-emergence loop. Such an understanding of the relationship between abstraction and emergence can be helpful in designing communities of autonomous agents that interact socially with each other and with humans, and may also be a helpful step toward understanding the phenomena of emergence and abstraction in general.

INTRODUCTION

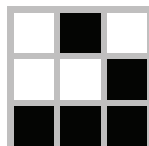
A number of different disciplines have taken on the task of studying emergent phenomena, trying to understand how and why they emerge, and delineating what makes emergent phenomena different from other phenomena exhibited by complex systems. Within computer science, much of this work has fallen under the auspices of artificial life (ALife). This subfield focuses on creating computer programs and simulations that exhibit qualities we otherwise attribute to living things, such as the ability to reproduce. A common environment for such work is cellular automata (CA), a grid where each cell on the grid is in a certain state at each tick of a system clock, and each cell's state at the next iteration is determined according to a set of rules that refer to its neighbor's states in the current clock tick (see (Sarkar 2000) for a survey). One of the earliest examples of this is von Neumann's self-replicating machine (von Neumann 1966), the goal of which was to create a theoretical machine capable of universal computation. This CA has the ability to produce any other cellular automaton if given a description in the proper format of the automaton to be produced. If the automaton is given a description of itself, it is thus able to reproduce itself. A reproducing CA was also developed by Christopher Langton (1984), whose goal was not to create a CA capable of universal computation, but rather the simplest possible CA still capable of self-replication. These automata's capacity for reproduction is a well-known example of emergence, in that the high-level phenomenon of reproduction emerging from the low-level rules of the system, where none of the low-level rules explicitly describe the process of reproduction.

Another classic example from ALife is the cellular automaton known as the *Game of Life*, first developed by John Conway (Gardner 1970). The

cells in this relatively simple CA have only 2 states, which are called alive and dead. A cell's state at the next iteration is given by three simple rules. Any cell with one or zero live neighbors is dead. Any cell with two or three live neighbors is alive. Any cell with four or more neighbors is dead. From these relatively simple rules, vastly complex patterns emerge. One of the better known is that of the glider (Figure 1), a pattern which moves one cell down and one cell to the right every four iterations (the direction of this movement depends on the orientation of the glider pattern). The high-level behavior of a unified pattern moving is not actually built into the system. Indeed, the automaton has no representation of this glider pattern, only the representation of the states of its cells. Rather, the behavior emerges from the interactions between individual cells in the system based on the rules that govern it.

These are a few examples of the types of emergence described in ALife. A system based on fairly simple, low-level rules exhibits some high-level behavior not directly or explicitly built into the system; the high-level behavior emerges from the low-level interactions within the system. It is important to note here that predictability has little to do with whether or not a phenomenon is emergent. As has been noted by Damper (Damper 2000), the property of self-replication exhibited by von Neumann's machine is not only predictable, it was in fact designed into the machine. This does not mean, however, that the property is not emergent. It is still emergent, because the high-level phenomenon of self-replication occurs as a result of interactions between low-level rules that do not explicitly describe the property of self-replication. It can be seen here that as the system exhibits emergent properties, an observer must be present to observe those properties and note that they are indeed emergent. The importance of level of detail and the role of the observer in emergence will be addressed later in this chapter.

Figure 1. A glider from Conway's Game of Life



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