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The Emergence of Art Systems

Cycles of Change in Art Styles Before and After the Renaissance

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Abstract

We studied changes in art styles related to changes in the surrounding society. In particular, we examined changes in art styles before, during, and after the Renaissance period. Art historians often subdivide each art period into Early, High and Late stages, as they describe a kind of cycle during the development of new, dominant styles. We compared these artistic cycles to models from complexity science, which show how systems move from chaos into the complex region at the edge of chaos from which emerges order. Eventually, the cycle reverses back into complexity or even into chaos, before a new cycle begins.

In order to account for these cycles in art styles, we subsumed many social and economic factors under two general system variables: *differentiation* and *centrality*. *Differentiation* refers to the amount of variety within a system, for example, the range of services in an urban system such as the city of Florence. Differentiation also refers to how a variety of skills and techniques are organised, say, through political and economic links among art patrons. *Centrality* is the extent to which a system is connected to other systems, and, hence, exposed to incoming information. Thus, centrality varied over time for a city such as Florence from the fourteenth to the seventeenth centuries, depending upon its links with other cities. We then showed how the ratio of differentiation to centrality accounted, at least in a general way, for cycles of art from the Gothic through the Renaissance to the Baroque periods.

1. Introduction

The general idea of change seems to be the most obvious and yet the most elusive of concepts in both the physical and social sciences. On the one hand, nature seems to be in a constant state of flux, never the same from moment to moment, exploding in surprising new directions, sensitive to the slightest breeze, the merest touch of another object. Some modernist abstract art seems to capture this almost random, fluctuating kaleidoscope of appearance, interaction, and change (Stella, 1986).

Yet, the primary goal of rational science is to detect orderly, fixed structures where change is predictable, and controlled through universal laws. The physical sciences, in particular, from the ancient Greek mathematicians to Renaissance scholars to Enlightenment researchers and modern experimentalists, have uncovered a variety of such predictable processes which govern the state of almost everything, from the tiniest ‘string’ of sub-sub-atomic particle theory to the expansion of the universe itself into multiverses. These processes which scientists have discovered seem to be governed by laws which are themselves unchanging. Much Renaissance art was an attempt to replicate these laws of reality, from using mathematical formulae to reduce three dimensions perspective to two dimensions, to mimicking the human form and its behaviour according to certain formulae (Stella, 1986).

Thus, there seem to be two regions within nature, simulated, in turn, by two extreme art styles—the region of constantly changing *chaos* sometimes found in post-modern art styles, and the region of relatively fixed order, exemplified by the elegant beauty of art in the High Renaissance. In the chaotic region, change seems quite unpredictable, and sensitive to the influence of every outside force. Within the region of order, on the other hand, change is more predictable and determined by laws which explain when and how change happens. It may be, however, that the appearance of both chaos and order is somewhat misleading, and more recent discoveries in complexity science have revealed underlying patterns even in chaos, and evidence that even the most ordered structures may be chaotic in the long term (Gleick, 1987; Murray & Homan, 1999).

The new science of complexity has discovered, also, that there exists, in addition to chaos and order, a third region between the region of less predictable chaos and the region of more predictable order. This intermediate region was first called "the edge of chaos", since it is within the orderly region but near the boundary with chaos (Kauffman, 1995: 86ff). More recently, this intermediate region has come to be identified with complex processes, and we will call it the region of *complexity* (Wolfram, 2002: 281ff). In this third, intermediate region, systems and their structures, and even the laws which govern change processes, appear to be emerging out of chaos into new patterns of order, a process known as *self-organisation* (Kauffman, 1994).

The three regions correspond to Wolfram's discovery that essentially all discrete systems, that is, systems based upon the interactions of discrete, separate subsystems, may be put into four classes: chaos corresponds to his Class 3 systems, complexity to his Class 4, and order to Classes 1 and 2 (fixed and periodic order). Much of the work on the Wolfram classes is concerned with the exploration of what goes on in each of the classes, using, as Wolfram did, computer simulations based primarily on cellular automata but including, as well, a wide variety of other discrete systems.

More recently, another group of complexity scientists, starting with the computer modelling of Duncan Watts and Albert-László Barabási, have studied the structure and behaviour of a specific type of system, social networks, again within each of three regions. Much of the study of networks grew out of investigations of the small-world phenomenon—why even casual acquaintances often have other connections to us (Barabási, 2002; Buchanan, 2002; Watts, 2003). Watts and Barabási found, midway between decentralized *nodes* which are close to randomness and more ordered systems of dominant *hubs*, the region of small worlds, made up of many smaller *clusters*. This intermediate region corresponds to what we are calling the complex region between chaos and order.

We will use the terms of chaos, complexity, and order for the three regions within which systems may exist, rather than Wolfram's four classes, or the Watts' and Barabási's terms of nodes, clusters and hubs, but the terms seem equivalent. In all cases, we are making the assumption that systems exist primarily within one of these three states. The overall movement from less order to more order we will call *social focusing*. That is, the less ordered chaotic systems are much less focused—in Wolfram's terms, they are very sensitive to initial conditions. Any slight changes in the environment sends the system off into an entirely new, unpredictable direction. Ordered systems, on the other hand, are more focused, in the sense that their output, their visible behaviour, resists change. The output of ordered systems is concentrated around a narrow variety of actions—it is focused. In between, within the region of order but at the edge of chaos, is the region of complex behaviour. Complex systems reveal a core of orderly behaviour, but they respond to outside forces by adapting and even generating new forms of order, while retaining their essential core structure. Hence, to move from chaos through complexity to order, is a process of becoming more focused, specifically, for social systems, to be more socially focused.

Our prime interest in this paper is how and why social focusing varied in the social systems which produced Gothic, Renaissance and Baroque art. Why do systems, in particular, social systems, move from one state to the other? In particular, why do systems of artists and their styles change from loosely connected artists working with their own styles, into several workshops, each with a certain style, to the stage when artists are expected to conform to a dominant style often dictated by centralized academies? Why, following a process of increased focusing. does the cycle of art systems then return from order back into complexity and even into chaos?

In the first part of the paper we will review some of the theories of change derived from the study of Wolfram classes found in cellular automata, as well as from attempts to move networks among the three structures of nodes, clusters and hubs. We will conclude this more theoretical section with our own explanation for change among the three regions, based on what we are calling the differentiation/centrality ratio. In the second section of the paper, we will apply our theory to changes in art styles, using as illustration the Gothic period before the Renaissance, the Renaissance period itself, and the following period of the Baroque.

2. Theories of Change in Social Systems

2.1 Cellular Automata and the Four Classes

Although cellular automata were invented by John von Newman in the 1940s, it was Stephen Wolfram's exploration of cellular automata in the 1980s which defined the classes corresponding to chaos, complexity and order (Flake, 1999: 232, 236; Wolfram, 1984, 2002). The simplest form of a cellular automaton is a row of ones and zeros—or a row of black and white cells. Each successive iteration of the cellular automaton produces another row of cells. The appearance of new rows is governed by a set of rules, such as, "If both cells adjoining a white cell are black then the white cell changes to black."

There are a finite number of such rules, all based upon Boolean logic, although the number of rules becomes very large very quickly as we make the system more complicated. Wolfram tested all such rules for simple cellular automata on a computer, over literally millions of iterations From these results, he discovered that there were only four possible types of systems, which he called classes. Class I systems ended up in a homogenous arrangement which never changed. Class II systems cycled endlessly through a fixed number of states. Class III systems produced random-like results with no obvious pattern, and where the states were extremely sensitive to initial conditions. Class IV systems were a mixture of local structures on a random-like background, and can be thought of as intermediate between the Classes I and II, and Class III (Flake, 1999: 237; Wolfram, 2002: 231ff). For this paper we have called Class III systems *chaotic*, Class IV *complex*, and Classes I and II *ordered* systems.

Wolfram then went on to study random samples of more complicated cellular automata—with several colours, in several dimensions, with much more intricate rules such as rules for change based on the state of non- adjacent cells, 'mobile automata' where cells change individually rather than simultaneously, systems without a lattice, and 'substitution automata' where new groups of cells are substituted according to a meta-rule. Somewhat to his surprise, the same four classes appeared, albeit in different proportions. Complex patterns, for example, were much rarer for the more complicated cellular automata (Wolfram, 2002: 51-113).

In his magnum opus, *A New Kind of Science*, he describes his experiments and also connects his results to a variety of other mathematical, physical, biological and social phenomena. His major discovery was that almost all phemonena seemed to be generated by simple rules, probably similar to the rules controlling cellular automata. At the very least, he discovered, all systems may be simulated by certain cellular automata, in particular by what mathematicians call "universal computers" (Flake, 1999: 467). He has shown that even a very simple Class IV system is a universal computer.

So, what is a universal computer? The underlying arguments for universal computing are both subtle and profound (Flake, 1999: 430-433). It can be proven that all *computable* systems may be simulated exactly by a universal computer such as a digital computer—if it has enough memory. This raises a further question—what is a computable system? It is a system which can process a series of yes/no questions (Flake, 1999: 447). According to Flake, some systems seem not to be computable, although he admits that cannot be proved. Most non-computable systems involve some degree of randomness where, by definition, it is impossible to predict what will happen next, hence impossible to determine a yes/no answer to a question about the the system. For Flake, this includes social systems, made up of a variety of people, each making decisions based on personal factors which cannot be completely analysed, so that there is always some inherent randomness and unpredictability in social behaviour.

In contrast, Wolfram argues that even apparently random systems are probably repetitive if observed over a long enough time period—possibly much longer than the age of the universe—but they are not random. Certainly all cellular automata are repetitive—eventually—and are precisely determined by the rules which govern what happens next. His argument for more complicated systems such as societies is that they may be reduced to individuals, which in turn may be reduced to biological processes, which are based on the interactions of genes, which depend upon molecular processes, and so on, until at some level the behaviour, in theory at least, is mathematically computable. If Wolfram is correct that all systems, even social ones, are at least approximately computable, then, since all computable systems may be simulated by some cellular automata, whatever happens in cellular automata may be generalized to real systems, including social ones.

At the very least, cellular automata can approximate real social systems. There is another principle, "universal approximation", also from mathematics, which states that any process may be approximated by certain kinds of networks, such as the neural networks found in biological organisms (Flake, 1999: 407), which means, at the very least, that what happens in cellular automata is approximately equivalent to what happens in social systems.

To make a long story short, for all practical purposes, the patterns of chaos, complexity and order found in cellular automata probably also occur in social systems. Hence, we are using the argument that what happens in the real social world may be understood—approximately—through various kinds of computer modelling, especially through the study of cellular automata.

Wolfram's conclusions based on cellular automata, then, helped us classify the states of social systems—such as those governing art styles—according to differences among chaos, complexity and order. Furthermore, using Wolfram's logic for simulation, there exist cellular automata which are universal computers able to mimic social systems. Unfortunately, most such simulations are very complicated. This complication can be reduced by altering the structure of the cellular automaton but it still seems much more artificial than the way in which natural processes of change happen in real social systems. Furthermore, since each particular cellular automata is a discrete system governed by a certain set of rules, his results are less helpful in understanding how systems change from one class to the other.

There are, fortunately, other kinds of computer models which seem more similar to social systems than the somewhat abstract cellular automata. In the next section we will review recent research on on the simulation of networks by computer models developed specifically to imitate social networks involved in the "small world phenomena." Although network models are very different from cellular automata, they appear to produce results which, again, fall into either chaos, complexity or ordered classes.

2.2 Network Theory

The small world phenomenon, though well known to anyone who has met a stranger who shares a common acquaintance, was first tested systematically by Stanley Milgram in the late sixties. By following the paths of letters sent from people in one part of the United States to strangers elsewhere, he was able to demonstrate that most people—in the United States at least—are connected to each other by a remarkably small number of links, perhaps as few as six (Watts, 2003: 37-39). In the nineties, Duncan Watts, a mathematician who later became a sociologist, decided to develop computer models of networks which would simulate the small world phenomenon.

The general study of networks goes back at least to Euler, an eighteenth century mathematician who used the idea of nodes and links to solve a geographic problem involving an island and several bridges in the nearby town of Königsberg (Barabási, 2002: 10-13). More recently, beginning during the 1930s, experimental studies of social groups by Moreno and his students led to the development of graph theory, a mathematical analysis of real world networks (Moreno, 1934). After World War II, Erdös, an eccentric, peripatetic mathematician, developed a somewhat narrower version of graph theory which applied only to random graphs, defined as graphs which grow by adding links at random. He showed that random graphs quickly form networks with very short path lengths between any two points, one of the characteristic of small worlds (Barabási, 2002: 14-18; Watts, 2003: 43-47). But, of course, people do not develop their networks randomly—they form clusters of friends and acquaintances based on those who live near them or who know someone they know. Watts' computer models were designed to simulate more closely real small worlds.

2.2.1 The Small World Problem

Watts started studying the small world problem by modelling three kinds of networks systems—he called them three worlds—corresponding to what we have been calling chaos, complexity and order (2003: 74ff). As Wolfram had already discovered,

> Very simple rules, at the level of individual actions, can generate bewildering complexity when many such individuals interact over time, each making decisions that necessarily depend on the decision of the past (Watts, 2003: 77).

Watts called the first world *Solaria*, named after a planet in Isaac Asimov's *Robot* books. In Solaria, the chaotic world, people are widely scattered, with few links among them, but even the addition of a few random links—approximately one per person—will connect everyone, as Erdös had already discovered. The network structure itself changed dramatically with the addition of a few links—it was sensitive to initial conditions, the key defining property of chaotic, Class 3 systems.

At the other extreme, in the ordered world of Caves—also named after a planet in the Asimov *Robot* series—people lived in tightly linked clusters with almost no links among clusters, so that the network was unconnected. But the structure of clusters remained relatively fixed, even when more links were added, since most links were among people who were already closely connected. The Cave world, then, corresponded to Wolfram's Class 1 ordered systems, where little structural change occurs no matter what happens. In a later model he was able to generate ordered networks which were periodic, corresponding roughly to a Class 2 system (2003: 84-85).

Between the chaotic world of Solaria and the ordered world of Caves, Watts was able to manipulate his computer models to simulate small worlds, that is, a complex world where people still lived in relatively isolated cave-like clusters but where even a few 'shortcut' links between clusters soon connected everyone, forming a system with short path lengths between each person. Watts concluded that this intermediate network with many clusters—neighbourhoods, families, workplaces—and a short path length between any two nodes corresponded to a small world. As in Wolfram's complex Class 4 systems, order remains within the clusters, but the overall structure gradually changes as a few shortcuts are added, and a new system emerges.

The shortcuts between clusters are what the sociologist Granovetter called *weak ties* among casual acquaintances (1973). Granovetter discovered that weak ties linking casual acquaintances were often more useful for finding employment than strong ties among neighbourhood friends. Residents already knew everyone in their neighbourhood—they needed the weak ties to link up with other job opportunities.

So, in the process of solving the small world problem, Watts had generated the regions of chaos, complexity and order, although he did not use those terms. He, and others working in this field, also found that the intermediate model of clusters connected by weak ties corresponded to many real world networks, from networks of academics, to movie actors, to electric power grids, to neural networks in worms. He also found that the transitions among the three regions in his computer simulations were quite abrupt, what he called phase transitions, corresponding to the transition among the physical states of gas, liquid and solids(2003: 80-81). Again, this resembled the very distinct regions of the Wolfram classes.

Now, while Watts could make his models move from one region to the other by changing parameters in the equations governing the output of the models, this was not too helpful in figuring out why real world systems move from chaos to complexity to order, because his model parameters seemed to have little correspondence with the real world (2003: 84, 87). Better understanding of change among the three regions came from studies of actual networks—such as the Internet—done by Barabási and others.

2.2.2 The Development of the Internet

The quite recent studies by on the growth of the Internet, especially the World Wide Web, reveal a bit more how social networks might change from one region to the other. Where Watts started with computer models of networks to see which ones simulated small worlds, Barabási examined changes in real networks such as the Internet and then attempted to simulate those changes with computer models (2002: 65ff).

Barabási discovered that in the early days of the Internet, the network consisted of loosely connected, scattered nodes, similar to Watts's Solaria. At this stage, the Internet was very fluid, sensitive to changes anywhere in the system, similar to what we are calling a chaotic system. At a later stage, during the early days of the World Wide Web, there were many fairly highly connected sites—browsers and other popular sites such as AOL—which in turn, had connections to other hubs, each arranged in the form of a hierarchy. This is analogous to Watts' small worlds, and what we have identified as an intermediate, complex stage.

Out of this complex network has emerged the current World Wide Web, which is dominated by a few very central hubs, such as Google and Yahoo, connected to a large percentage of other nodes, a much more ordered stage, analogous to a giant cave in Watts' models, or to a leader centred structure in small group studies. If this trend continued, then one hub, such as Google, eventually would control the entire Internet, with little or no change permitted, hence, an extremely ordered network. Certainly, even at this point, it is difficult for new nodes to have much power without being attached to one of the very central hubs, and so these dominant hubs do control much of what happens on the Internet.

As Barabási pointed out, however, there is a kind of negative rate of return which sets in when one or a few hubs dominate. The network is very ordered but if the dominant hub were disabled, say with a computer virus attack, the entire network, dependent as it is upon that dominant one, would collapse. Furthermore, the central hub sometimes becomes congested, causing delays in getting to other nodes, for example, when many users are using them at the same time (2002: 192-193). As well, that very order may becomes so rigid that the system is unable to respond to new demands (Barabási, 2002: 201). Eventually, the cycle reverses and other nodes and hubs appear which provide faster and more efficient links. In effect, Barabási predicts that the current system of the Internet will likely break down, back at least into what we call the complex region of many hubs, before another more ordered system emerges.

Barabási uses two terms to describe the different types of network structure (Barabási, 2002: 70ff). The early network stage of widely scattered nodes he calls *scale networks*, meaning that there is an average number of connections for each node, with a few having a slightly larger and few with a slightly lower number of links. The result of plotting frequency of links against the number of nodes with that frequency is a "normal" or Poisson distribution—a hill with steeply falling sides. The centre of the distribution, the average number of links, becomes the scale for the network. This is typical of more random based networks, close to the region of chaos.

For later stages, a few nodes have a high number of links with a declining number of links for the remaining nodes. This produces the so-called *power law* distribution which resembles a ski slide falling from a high number of connections to a gradually decreasing number of links. In this case, it is not meaningful to speak of an average number of links to describe the distribution, and so the distribution is *scale-free*. Since Barabási's original research, power law distributions have been discovered in a myriad of networks, from neural systems to the distribution of users of downtown shelters (Gladwell, 2006). In each case, a few nodes have a disproportionate number of connections, typical of more ordered networks.

Barabási's goal, then, was to simulate and discover parameters—what he called 'principles' in his computer models—governing the change of structure from scale to scale-free networks, from chaotic systems with near random nodes to ordered hubs. Barabási's first principle was the assumption that change is the result of adding nodes—not links, as Watts had done—at random. So, Barabási argued that the Internet network grew in its early years simply because new websites were created, essentially at random.

Secondly, was the principle of "preferential attachment,' which assumed that the more popular, connected nodes, attracted more new links—the rich became richer. As Google and Yahoo became more popular, more and more websites included a link to them, to ensure that people found them. This moved Barabási's model of the Internet from scattered small hubs—a chaotic system—into the intermediate stage we call complexity, consisting of several "richer" hubs.

Finally, Barabási speculated, networks would evolve into the ordered stage of a few hugely dominant hubs, only when there were 'crawlers'—mechanisms such as 'spiders' and 'indexers' used by browsers—which discovered and linked new websites. In the social world these might be explorers, travel agents, and other independent movers who link minor nodes to major ones. Using these three principles, Barabási's model of the Internet moved from chaos, through complexity to became more ordered and rigid, as all new nodes became connected to a few central hubs through a hierarchy of lesser hubs.

Both Watts's and Barabási's models were able to simulate transitions among the regions but they did it by altering parameters within the mathematical equations governing their computer models. Watts' parameters were rather obscure exponentials in his earlier models or probabilities in his later ones. To explain how networks such as the Internet grew, Barabási introduced principles into his models which were still somewhat arbitrary assumptions about individual behaviour—nodes are added at random, the rich get richer; crawlers.

We are suggesting in this paper that there are other, more social variables which lead to the process of change from chaos through complexity to order and back again. The interaction of these social forces produce, we believe, cycles of change. In the next section we discuss the social process involved in the interaction between two such fundamental variables, summarized by the differentiation/centrality ratio. We will also show how this ratio is related both to the models of cellular automata investigated by Wolfram et al., as well as the networks theories introduced by Watts and Barabási.

2.3 Cycles of Change and the Differentiation/Centrality Ratio

Before introducing the idea of the differentiation/centrality ratio, we will review two underlying, apparently contradictory yet fundamental, processes in nature. The first process is *self-organisation*, the tendency which drives systems out of chaos, through complexity, into order. The second process is the production of *entropy*, the tendency of all systems to run down, to move from order back through complexity into chaos. The differentiation/centrality ratio, we argue, determines which process dominates. If the differentiation/centrality ratio is greater than one, self-organisation takes over; if the ratio is less than one, entropy takes over. If the ratio increases and then decreases, the result is a cycle from chaos to chaos, peaking with order, with complexity at the shoulders of the cycle. Of course, the cycle may not go all the way back to chaos before rising again to order. First, a brief summary of the two processes of self-organisation and entropy.

2.3.1 Self-Organisation

The new science of complexity really began with attempts to explain self-organisation, how systems, especially living, biological and social ones, are able to move, seemingly spontaneously, from disorder to order. Stuart Kauffman, especially, was—and remains—fascinated with the emergence of new order out of chaos. His computer simulations seem to show that self-organisation most likely happens within the more complex region between chaos and order. He has not explained why this happens but believes that as a result of biological evolution—including social evolution—systems are more likely to exist in a state of complexity, hence more likely to generate self-organisation. (Kauffman, 1994). The important point is that order seems to emerge during the intermediate stage of complexity.

Again, we will use the term increasing *social focusing* to describe self-organisation, the process of moving from chaos into order, of order emerging from disorder.

2.3.2 Entropy

The concept of increasing entropy is a much older concept. Ever since the nineteenth century study of heat transfer and the development of the Second Law of Thermodynamics, it has become accepted that it is normal for entropy—loss of control and an increase in unpredictable randomness—to increase in any transfer of energy or information. In simple terms, this means that some energy or information is lost at each transfer so that all processes are essentially irreversible. Entropy has been increasing in the universe since the Big Bang and this may explain why the arrow of time runs one way—downhill, according to the Second Law (Greene, 2004: 143ff; Prigogine & Stengers, 1984: 257ff). You cannot put Humpty Dumpty, the smashed egg, back together again. In our terms, there is a tendency for all systems to move out of order into complexity and eventually all the way back to chaos. Overall, a sense of focus is lost, and the system becomes unfocused.

During the intermediate stage of complexity, however, it is possible for self-organization to overcome entropy, for systems to re-emerge into new order, to generate more social focusing. An example in the social world is when an organization begins to collapse but then emerges with a new form of order, a new sense of focus. The important qualifications, however, for self-organisation, is that new energy is needed to replace the energy lost because of increasing entropy. It costs, in other words, to move from entropy to self-organisation. Somehow the system needs to bring in energy from outside to increase social focusing, to generate self-organisation and increase order in that particular system. For the larger suprasystem supplying the energy, of course, the process of increasing entropy is speeded up in order to cover the cost of self-organization in the smaller system.

These two meta-laws of self-organisation and entropy production, then, tend to move systems back and forth among the three regions, in a kind of repeated cycle where systems, especially social ones, move out of chaos into order, and back toward chaos. Between the two extremes of chaos and order there are periods spent in the intermediate region of complexity. The question remains, however: why does one tendency or the other dominate at any given time? Why do systems sometimes experience self-organisation while at other times the production of entropy takes over? Why does the degree of social focusing vary? Our explanation is based on the differentiation/centrality ratio.

2.3.3 The Differentiation/Centrality Ratio and Social Change

We'll begin with a brief description of the two variables of differentiation and centrality. Differentiation refers, in its broadest sense, to the amount of *internal* variety within a system, such as the variety of occupations within a city such as Florence. For a group of artists, differentiation might refer to the different kinds of techniques available to them as they set out to do a painting. It is important that the variety of occupations and techniques are available to the system, so the concept of differentiation also includes an internal structure where the variety is connected and coordinated. As we have learned from network theory, that structure varies from region to region. In the chaotic region, the differentiation structure is a near random, haphazardly arrangement of connections. In the region of complexity, the structure consists of several subsystems of coordinating small hubs loosely connected to other clusters. Finally, in the ordered region, the structure is a giant hub which controls and coordinates almost all of the other nodes.

Centrality refers to the *outside* variety of threats and demands generated by links to other systems, for example, the ties connecting Florence to other cities during the fifteenth and sixteenth centuries. For individual artists, personal centrality refers to their connections to other artists, and especially to patrons who supply them with money—along with requests for works of art. The concepts of differentiation and centrality are fractal, that is, they are similar at every scale. Thus, the internal differentiation and external centrality of each individual subsystem is similar to the overall differentiation structure and centrality of the entire system. In turn, each system, in turn, is part of even larger suprasystem, so the differentiation/centrality ratio may be calculated at any level in order to predict what happens at that level.

That ratio of differentiation to centrality for a given system, we argue, determines whether self-organisation or entropy dominates, and, hence, whether the system moves from chaos to order or in the reverse direction. When the differentiation/centrality ratio is much greater than one, it means that differentiation is much larger than centrality, and so the system becomes more focused, quite ordered and organized. This happened in Florence during the early sixteenth century when the city contained a wide range of trades, coordinated by a strong central government under the Medici—that is, differentiation was high. At the same time, centrality was relatively low—the city protected itself against outside military threats and unusual trading demands.

At the other extreme, when the differentiation/centrality ratio is much less than one, that is, when centrality is much larger than differentiation—then the system is less focused, more chaotic as the forces of entropy take over. During times of invasion centrality increased—cities such as Florence in the later fifteenth century were suppressed by outside forces because they had insufficient differentiation to repel the attackers. The city lost its focus, and became more disordered.

In an analogous fashion, when a group of artists are asked to meet the demands of patrons who suddenly have a lot of money, in effect, the increased centrality of the artists exceeds their differentiation abilities. As a result, the differentiation/centrality ratio falls, and the artists become unfocused. At first, the lowered social focusing may result in innovative styles, as the group of artists move into a more complex region. If the differentiation/centrality ratio is too low, however—that is, centrality is much greater than differentiation—then the artists may produce very shoddy and degraded work which no longer conforms to a certain accepted style, because the artists as a group lack the differentiation to handle the increased demands. Their differentiation/centrality ratio is so low they have moved from order all the way back into chaos..

In between, when differentiation and centrality are approximately matched, we are in the region of complexity where new systems gradually emerge. This happens for cities when they gradually increase their skill repertoire, while trade opportunities increase at approximately the same rate. Similarly, a group of artists who have a variety of skills equal to or slightly greater than the variety of demands for their works, will behave in complex ways, as different schools arise for awhile then decline in importance. Eventually, however, if differentiation—the techniques available to artists—continues to increase and becomes coordinated, along with a constant demand—centrality—we would expect one dominant style to emerge and dominate, as the differentiation/centrality ratio increases and moves the system into a new type of order. The system is more focused and self-organisation dominates.

The reverse process, the production of entropy, takes over when differentiation begins to fall and centrality rises so that the system becomes less focused. Over time, people may leave formerly successful cities for new centres of innovation, or unused skills are forgotten, in both cases, lowering differentiation. At the same time, defensive barriers may weaken, and/or outside armies develop new weapons and may conquer the city, both having the effect of lowering centrality. the combined effect of lowered differentiation and higher centrality means that the differentiation/centrality ratio falls, the system becomes less focused, and moves out of order back toward complexity and even chaos.

How are the cycles produced by changes in the differentiation/centrality ratio related to cellular automata and network studies of small world phenomena? Wolfram's main goal was to classify the types of systems produced by cellular automata, and by extension, all systems. He was not especially concerned with how systems shift from one class to another but rather how to make one system simulate another. Still, it would appear that Wolfram's two terms of rules and initial conditions correspond roughly to our two terms of differentiation and centrality. In general, Wolfram found that the more complicated and varied are the rules for cellular automata, with a given set of initial conditions—that is, when the differentiation/centrality ratio increased—the more likely the system was to produce one of the two ordered classes. On the other hand, when initial conditions became more random and unpredictable—that is, centrality increased—the more likely that the system also became less predictable and more chaotic, similar to what happens when the differentiation/centrality ratio falls. At least in Wolfram's studies, it is not clear that there is a linear relationship between the ratio of rules to initial conditions and the three states of chaos, complexity and order. It is important to note, however, that while the two sets of terms are not identical, at the very least they do not contradict each other. Wolfram might also argue that his studies of each type of system is much more precise than our more general relationship between internal and external variety, between differentiation and centrality.

The comparison with network theory is a bit more straight forward. In systems with a few scattered nodes, loosely connected to several other nodes, the results are chaotic—the world of Solaria. Here differentiation is low and the system is very sensitive to any new input—increased centrality—which alters the number of nodes or their interconnections. Again, the low differentiation/centrality ratio produces chaos.

In the intermediate stage, that of clusters connected by a few ties, we find the complex systems of small worlds. Each cluster has just the right amount of differentiation to handle incoming information—differentiation is approximately equal to centrality. Out of this complex stage of the later Internet, developed the more ordered system of the World Wide Web.

As the World Wide Web developed, it has become a highly organised system dominated by one or a few hubs coordinating a huge number of different sites, so that differentiation is quite high At the same time, the Internet has relatively lower centrality—less new information is entering—especially as more and more restrictions are introduced to restrict what kind of information is permitted.

So it would seem that the discoveries in complexity science based on cellular automata and networks are at least consistent with our theory of social change based upon the differentiation/centrality ratio. Those changes seem to occur in cycles and, hence, may be an explanation for historical change in general and for the resulting cycles of changes in art styles, the topics to which we now turn.

2.3.4 Cycles in History and the Differentiation/Centrality Ratio

In most social systems, differentiation and centrality change rather slowly. As well, social systems eventually adjust to differentiation/centrality ratios which are very high or very low, and the result is a succession of cycles as the system moves out of chaos, through complexity to order, then falls back, at least into complexity, before a new type of order emerges.

The resulting cycles are really *near*-cycles, since, over the long term, there is an accumulation of differentiated skills which enable later social systems to adapt more easily to new influxes of information. Only rarely does an entire society fall back entirely into chaos. As well, briefer cycles are superimposed upon longer-time mega-cycles so that the individual mini-cycles never quite return to their earlier state. To use the term from complexity science, this cyclical phenomenon over time is *fractal*, where the same shape is visible over any time period, so that mini-cycles rise and fall on mega-cycles. For convenience, however, we will usually use the term cycles, realizing that they are actually near-cycles.

Figure 1, below, shows an abstract example of any system passing through a long cycle of change, moving from Stage 1, a chaotic phase, up to the highest point of order at Stage 6, before eventually moving back to chaos at Stage 11. Along the way, the system moves through mini-cycles around the three regions of chaos, order and complexity.