Some Regularities in Human Group Formation and the Evolution of Societal Complexity

KRISZTINA KOSSE

Krisztina (Krudy) Kosse was born in Budapest, Hungary on December 8, 1943. After moving to Great Britain in 1964, she studied under Stuart Piggott at the University of Edinburgh where she received her MA. She earned her Ph.D. in 1977 at the University of London, Institute of Archaeology with a dissertation on the settlement ecology of Neolithic cultures in Hungary published by British Archaeological Reports in 1979. That research, a long-term interest in classical civilizations, and a fascination with understanding how human societies are organized and organize themselves over time, led to her subsequent research and publications in the development of hierarchical political structures and the organization of regions. Dr. Kosse moved to the United States in 1974 and joined the Maxwell Museum of Anthropology at the University of New Mexico, where she was first Associate Curator and then Curator of Collections. At that time, I served on the Anthropology Department faculty and knew her as a colleague.

In contrast to most of her American-trained colleagues, Dr. Kosse approached questions about the development of ancient civilizations from an interdisciplinary, global, comparative perspective, and she meticulously examined hundreds of ethnographic cases to provide cross-cultural analyses. Dr. Kosse's thesis, which is shared by scholars internationally, is that scale is an independent measure of complexity based on the biological limitations for processing information available to Homo sapiens. Hence there are scalar thresholds that require structural reorganization. One common form of structural reorganization, that reduces scalar stress, is the creation of hierarchies. Dr. Kosse first outlined her approach in publications aimed at those interested in ancient civilizations. She found that there was also an avidly interested audience among those of us who study "mid-range" societies; those societies that did not develop state governments. Her methods and insights are useful to those of us who want to understand if the dimensions we use for observation obscure the order we seek or if and in what ways, natural behavior varies as scalar thresholds are reached. Dr. Kosse's tragically untimely death, of cancer, in 1995 deprived us of a brilliant guide.

Linda S. Cordell
University of Colorado Boulder

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The emerging science of complexity suggests that Darwinian theory alone may not provide a complete explanation for the evolution of complexity. In this paper human social systems are compared to sparsely connected K = *2 networks where order emerges from the restriction of interactions among elements. The organization of human systems both resembles and differs from the behavior of* K = *2 networks. The differences derive, it is suggested, from the evolutionary history of the human information processing system. © 2001 John Wiley & Sons, Inc.*

Recent findings in a number of different branches of biology suggest that Darwinian theory may not provide the whole explanation for the evolution of complexity in nonlinear dynamic systems [1; also see references in Mittenthal and Baskin (2)]. According to Darwinian theory, evolution proceeds through the accumulation of small, gradual changes as a result of natural selection acting on heritable variation. Regularities in pattern formation observed in the evolution of form and structure are not, however, explicitly addressed by the theory. A more complete account of the evolution of complex systems may require a marriage between Darwinian theory and the findings of the emerging science of complexity [1,3]. In this article I suggest that the marriage between Darwinian theory and the emerging science of complexity provides an important theoretical missing link, and Kauffman's [1] $K = 2$ networks a useful initial model for the interpretation of the evolution of social complexity. In return, human social systems, which exhibit regularities not observed in the other complex physical or biological systems so far examined by the emerging science of complexity, may provide a better understanding of the human information processing system. In this article, I attempt to show how the organization of human systems both resembles and differs from the behavior of $K = 2$ networks. In human systems, as in other complex systems, complexity derives from the interaction of the constituent elements. The dissimilarities are, it is suggested, due to specific evolutionary limitations peculiar to the human information processing system.

SOME FINDINGS OF THE EMERGING SCIENCE OF COMPLEXITY

Studies of nonlinear dynamic systems suggest that purely local interactions among the elements of a system may lead to the emergence of large-scale or global complexity [4, pp. 325]. It has also been observed that complexity emerges only at a very narrow range of interconnections between the constituent elements. If the number of connections between elements is too low, the system remains stable or "frozen," and no evolution occurs. If the interconnections are too rich, the behavior of the system becomes unpredictable or "chaotic." Self-organization and complex behavior seem to appear at a "razorblade thin" edge between much larger regions of stability and chaos [3, p. 308].

Some of these findings derive from Kauffman's work [1] with random Boolean networks as models for cell differentiation during ontogeny. He has found that although the behavior in $N = K$ networks is unpredictable, order emerges "spontaneously" in $K = 2$ networks, that is, when each element only receives input from two other elements. He has also found that in $K = 2$ networks both the length and number of state cycles (attractors) are reduced to about the square root of the number of elements in the network. By contrast, the number M of state cycles in $N = K$ networks, although still relatively low, is higher: N divided by the logarithmic constant e. $K = 2$ networks are also relatively stable to small perturbations. According to Kauffman [1, p. 81], relative stability is due to the development of "frozen" cores in the system. Although small perturbations may affect the behavior of some of the elements of the system, the larger "frozen islands" remain unchanged, and the system returns to stability. Nonetheless, the system is sensitive to outside influences: it is evolvable. Kauffman [1, p. 83] suggests that the genome may approach the behavior of $K = 2$ networks, because the genes are sparsely connected (each gene is regulated by ca. 10 other genes), and because canalization introduces a bias into the switching rules.

Interactions in human groups may also approach the behavior of $K = 2$ networks. Observations in a number of societies at different levels of complexity suggest a significant increase in dispute frequency and a correspondingly precipitous decline in decision-making quality, not infrequently resulting in the eventual disintegration of cooperative behavior, with unregulated interactions due to increases in group size [5]. What Johnson [5, pp. 394–395] terms scalar stress appears already when group size exceeds ca. six individuals. Similarly, in a n-person Prisoner's Dilemma game, Boyd and Richerson [6] find that reciprocity tends to break down in groups larger than ca. 6–10 individuals. In a study specifically designed to measure interactions in a formal organization (among crew members on board an ocean-going research vessel), Bernard and Killworth [7, p.164] have found the mean number of direct communicants for individuals to be 7.27 people. The limitations on the number of direct communicants are the same and probably derive from the limitations of the human short-term memory [8].

Empirical data thus indicate that human groups, not unlike genomes, are relatively sparsely connected networks. It is suggested here that social evolution is essentially the successive imposition of additional canalizing functions on interactions with increases in network or group size. As in $K = 2$ networks, canalizations maintain the "frozen cores" and thus the stability of the system otherwise threatened by the introduction of new elements and interactions between the elements. Human organizations also exhibit certain regularities that depart from expectations, based on the behavior of $K = 2$ networks. In human organizations, (1) the thresholds where canalizations occur seem to exhibit a certain regularity of behavior; (2) the number of major attractors seems to remain constant despite increases in system size; and (3) beyond a certain system size, a top regulatory unit emerges that remains constant in size despite increases in total system size.

REGULARITIES IN HUMAN GROUP FORMATION

Canalization, or the channeling of interactions, in human groups occurs through the formation of subgroups. The criteria used for subgroup formation may vary, but generally distinctions based on age and sex differentials are used first. As Johnson [5, pp. 401–404] has shown, when groups increase in size, decision-making and interactions between subgroups are first channeled through the heads of nuclear families, then elders of the extended family, and later through clan or descent group representatives or similar, still selected by egalitarian criteria. Once permutations according to egalitarian differentials are exhausted, the maintenance of cooperation requires the creation of formal hierarchies.

Regularities in Threshold Behavior

Previously I attempted to define the critical thresholds in human group formation and evolution and suggested that thresholds based on regularities in the human information processing system would be roughly the same in most classificatory schemes regardless of content and crosscultural differences [9]. One of the thresholds not included in the previous article was Birdsell's [10] "magic number" of 25. This threshold was omitted because I could find no reference to it in ethnobiological classificatory systems. Whether or not this threshold exists but is as yet undetected in ethnobiological classifications, it does seem to be present when small group formations are studied in band societies. With the inclusion of Birdsell's "magic number" as a threshold, the previously suggested series of thresholds exhibit a certain regularity of behavior: the successive thresholds seem to scale according to the following equation:

$$x_{n+1} = 7^{n+1}/2^{(n+1)/2},$$

where x_{n+1} are the successive thresholds and $x_1 = 7$. The observed and predicted thresholds using the equation are shown in Table 1.

TABLE 1

Observed and Predicted Thresholds in Human Group Formation

Observed Thresholds	Thresholds Calculated with $x_{n+1} = 7^{n+1}/2^{(n+1)/2}$, where $x_1 = 7$
7 ± 2	7.00
25 ± 5	24.50
150 ± 25	121.20
500 ± 100	600.25
2500 ± 500	2969.43

It should be noted that the suggested regularity is based on only a relatively few empirically observed thresholds, and in addition, the ranges for the observed thresholds are relatively wide (Table 1). The constant 7 derives from Miller's limitation on the short-term memory cited earlier and is only an approximation that needs fine tuning. Nonetheless, the suggested regularity makes predictions about other thresholds possible, which can, in turn, be checked against empirical evidence. Once the thresholds can be determined with more accuracy, it is hoped that a more precise equation can be worked out. It may also be noted that the equation which shows the limiting role of scalar stress above the relatively low figure of ca. 7 suggests that human systems are indeed sparsely connected networks. Finally, it may be pointed out that the lower thresholds, ≤150, are relatively ancient. Based on a close statistical association between neocortex size and group size, the 150-threshold limit was already present *in Homo erectus* ca. 300,000 years ago [11, p. 185].

Regularities in Attractor Behavior

A $N = K$ network of 500 elements can assume 2500 different states and ca. 185 attractors or different patterns of behavior. Such a network would be extremely sensitive to initial conditions and would thus be essentially chaotic. In a $K = 2$ network of the same size, the number and expected length of state cycles (attractors) falls to ca. 22. This network would remain stable "in the face of almost all minimal perturbations" [1, p. 81]. The number of attractors predicted by using Kauffman's $K = 2$ model is shown in Table 2. It may be noted that new thresholds appear when the number of attractors approximately doubles. The thresholds may be seen as potential areas of instability at points of bifurcations or phase transitions. At these points, the system may collapse or with additional canalizations assume greater complexity. If the thresholds in human group formation do indeed follow the suggested pattern, the evolution of social complexity may be seen as successive self-organizations in evolving complex systems at the boundary between order and chaos.

TABLE 2

Threshold Sizes, Number of Attractors, and Presence or Absence of Formal Hierarchies

Observed threshold size	No. of attractors predicted using K = 2 model	No. of observed major attractors	Presence of formal coordinating unit
2500	50.00	7	Yes
500	22.36	7	No/yes
150	12.25	7	No
25	5.00	7	No
7	2.65	7	No

Although the number of attractors predicted by the $K = 2$ model may provide a reasonable description for the total number of subgroups in a system, empirical evidence suggests that in human groups the number of major groups is much lower, and, what is more, it remains constant despite increases in system size. Studies of formal organizations [12, p. 205] and crosscultural studies of societies at different levels of complexity [13] all agree that the number of major hierarchical levels does not exceed ca. 7. Although the number of subgroups may and does increase with increases in the number of elements, the number of major hierarchical levels remains constant. Thus, the number of major attractors in human systems is maintained at ca. 7, although total group size may reach millions. As has been suggested before [9], the limitation on the number of hierarchical levels is again probably due to the relatively limited span of the short-term memory [8], which, in turn, is probably the result of long-term selection for relatively fast response to external fluctuations. Threshold sizes and the number of attractors predicted by the $K = 2$ model and the number of major attractors observed in human organizations are shown in Table 2.

Hierarchy Formation.

Despite increases in the total number of genes, the genome is maintained in the orderly regime because it is a relatively sparsely connected canalized network. As the number of genes increases in different species, so does the number of cell types, although at a relatively slow rate: the number of cell types (attractors) remains approximately the square root of the number of total elements (genes).

Human systems are also relatively sparsely connected networks, where order is maintained through successive canalizations with increases in the number of elements. In human systems, however, the number of major attractors also remains the same. With increases in system size but no corresponding change in the number of major attractors, attractor length must increase. As attractor length increases, so does response time to fluctuations. Slower response will eventually lead to a loss of effectiveness in competition with coevolving groups. With continued growth, a point will be reached when the system either disintegrates or develops a new coordinating unit of limited size and therefore limited attractor length.

Empirical evidence suggests that this point is reached when total community size exceeds ca. 2000–3000 people [9]. The presence of formal hierarchies has also been observed in groups of more than 500 but less than 2500 people [14]. Whether or not formal hierarchies appear between these thresholds probably depends on historical circumstance: e.g., the nature of local resources and competition with coevolving groups. Although canalization can be achieved between these thresholds using egalitarian criteria, formal hierarchies are generally more effective in competition. As shown in Table 2, a top coordinating and decision-making unit emerges when the ratio of predicted and observed number of attractors exceeds 7, although it may emerge earlier, that is when the ratio is just above 3.

Empirical evidence also shows that the size of the top coordinating or decision-making unit is indeed limited. According to crosscultural evidence, the size of the topmost decision-making unit does not exceed 500 people and remains the same despite any increase in total system size [15, pp. 249–250; see also references in Kosse (9)]. The limited size of the topmost decision-making unit together with the limited number of major hierarchical levels assures faster, and thus more effective, response to fluctuations.

POTENTIAL TESTS

Indirect support for the increase in the length of attractors comes from Blau's [12, pp. 204, 213] observation that social differentiation increases with system size, but it increases only at a decelerating rate. As Johnson [5, pp. 413–414] has demonstrated, this rule also seems to hold crossculturally: the ratio of administrative officials decreases with increases in group size. Johnson [5, p. 413] attributes the decrease to successive expansions in basal unit (largest subgroup) size. As basal unit size increases with each successive canalization, so does the length of the attractors.

Although indirect support is useful, the model still remains to be tested directly. There are, at least, two potential tests: (1) thresholds beyond those examined here can be calculated and tested against empirically observed data to see whether or not additional canalizations occur at the predicted thresholds; and (2) if the thresholds reflect regularities in the human information processing system, there should be a way to tie them in with the functioning of human memory and, ultimately, with the organization of neural circuits.

Some data are available for testing the predicted thresholds both in social organizations and in human memory. In an analysis of 26 prestate societies in the Americas, Upham [16, p. 355] finds a significant increase in organizational complexity measured by seven variables at the threshold size of 10,679 $\pm$ 2,494. Upham's threshold is close to the next threshold, 14,706, predicted by the equation. Further studies to test the predicted threshold are, however, still necessary. The variables used in measuring complexity are themselves controversial or at least subject to debate. According to Simon [17, p.106], empirical evidence suggests that highly trained experts (e.g., chess players at the grand master level, skilled diagnosticians) operate with a memory size of ca. 50,000 items in a single domain. The predicted threshold using the equation is 72,815. Whether or not this predicted, and admittedly approximate, figure falls outside the acceptable range of uncertainty will have to be checked against empirical data.

As to the organization of the human memory, there are as yet more questions than answers. One of these questions is how are the thresholds organized in the human memory? Specifically, how is the increasing number of thresholds collapsed into just a few major categories with increases in domain size? Is there an intimation here that human memory also operates as a relatively sparsely connected biased network, with the hierarchical levels as canalizing functions? Kauffman [1, p. 81] suggests that although the number of attractors may be relatively large, most "states fall within the basins of only a few attractors." Is there possibly an additional switching rule that regulates the attractors, at least in human systems, by attempting to keep the number of major attractors to no more than ca. 7? Or is it possible that human long-term memory has a limit of ca. 73,000 items organized in seven major levels in a single domain? Human social systems can, of course, grow to millions. The seven major hierarchical levels are preserved, however, through successive reclassifications. As classificatory schemes of both the natural and social worlds ultimately derive from the regularities of the human information processing system, it is predicted that a better understanding of the organization of the human memory will also lead to a better understanding of social organization, and evolution.

CONCLUSIONS

It has been suggested that human organizations may approach the behavior of $K = 2$ networks, where the system, relatively sparsely connected, is maintained in the orderly regime through successive canalizations on interactions with increases in system or network size. Human systems also differ from $K = 2$ networks and exhibit regularities not observed in other complex systems. It has been suggested that some of the regularities derive from the organization of the human memory. Further tests of the proposed regularities require a more detailed understanding of the human information processing system. If there are indeed regularities in human group behavior, a demonstrable link must exist between these regularities and the organization of human memory.

Whether or not the suggested model turns out to be true, the new science of complexity offers some hope for cooperation between practitioners of the sciences and humanities. Historians and prehistorians have long known that events may be singular, outcomes unpredictable, and most importantly, that history matters. What a marriage of Darwinian theory and the science of complexity can offer is a better understanding of the hidden and hitherto unsuspected regularities that underlie some of the chance events, unpredictable outcomes, and particular histories.

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