

Dynamic Constancy as a Basis for Perceptual Hierarchies

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RUNNING HEAD: Dynamic Constancy in Perceptual Hierarchies

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Abstract: Bateson's difference-based epistemology can be simulated by a Boolean network model. Bateson proposed that taking differences in differences would produce emergent hierarchies of knowledge. This study simulated Bateson's proposal by taking differences in differences in a Boolean model. The crucial result is that constancies in the dynamics of the flow of differences in the model (1) define perceptually comprehensible categories of visual forms and (2) that higher-order constancies arrange these categories into a perceptually comprehensible hierarchy. We propose Dynamic Constancy as a new Gestalt-like organizational principle in perception.

KEYWORDS: perceptual categories; epistemology; Bateson; Boolean networks and landscapes; Gestalt organization.

A dynamic system is characterized by a flow of changes over time. In a Boolean system these changes are binary, between two values, 0 and 1; they represent what we are calling here a flow of differences. A Boolean system generates a landscape of basins of attraction each of which, typically, consists of tributaries feeding into attractors. Malloy, Jensen, and Song (2005) have mapped Gregory Bateson's difference-based epistemology onto an NK Boolean system (Kauffman, 1993); particularly relevant here, they proposed a way to represent attractor cycles in a Boolean dynamic system as visual patterns. Bateson, using the map/territory metaphor to distinguish between knowledge and what is known, proposed that what gets onto maps are differences and these differences and their transforms are "elementary ideas" (2000, p. 463). Moreover, Bateson goes on to note that "these differences are themselves to be differentiated" (2000, p. 463). Bateson takes the differentiation of differences even further, making it an important foundation of epistemology by proposing that the process of discovering relationships in the patterns of differences in differences leads to the emergence of a hierarchy of differences with important consequences for mind (see Bateson, 2000, pp. 454-471; 2002, p. 106). Bateson (2000), pp. 463, 464) proposes a mental experiment for the reader:

Let me invite you to a psychological experience, First note that differences in texture are different (a) from differences in color. Now note that differences in size are different (b) from differences in shape. Similarly ratios are different (c) from subtractive differences.

Now let me invite you... to define the differences between "different (a)," "different (b)," and "different (c)" in the above paragraph.

Malloy, Jensen and Song simulated the process of differentiating differences by building an analytic tool, TAO, that uses the XOR operator to find the discrete analogue of the first derivative of the flow of differences in attractor cycles. To examine Bateson's proposal, above, we extend that logic to compute higher order derivatives by applying the TAO operation recursively to the output of TAO, thus generating higher-order derivatives of attractor cycle dynamics. In the Boolean case, both the dynamics of an attractor cycle and its discrete derivatives are expressed as matrices. As an example, assume the first derivatives of a set of attractors are exactly equal (their first derivative matrices are equal). That equality implies that they share some kind of constancy in their dynamics. We then can sort attractor cycles into categories based on these dynamic constancies where all the attractors in a particular category have equal first derivative matrices but their first derivative matrices are different from those of the attractors in other categories. This sorting can be done based on first, second, third, or higher-order derivative equality; thus there is, potentially at least, a hierarchy of possible categories. The question is whether these model-defined hierarchies correspond, as Bateson suggested, to human knowledge. Knowledge is expressed in this case as perceptual judgments. In this study three realms of description converge on the concept of emergent levels in knowledge: Batesonian epistemology, a Boolean model, and human perceptual experience.

DIFFERENCES IN DIFFERENCES

Higher order derivatives

Clearly, differences are the basis of a Boolean system. An NK Boolean system consists of N nodes each taking inputs from K nodes. At any moment, T, the state of the

N nodes is given by a state vector T (e.g., $S_T = \{0110\dots\}$). As the system changes dynamically from T to $T+1$ to $T+2$, ..., the state vectors, $S_T, S_{T+1}, S_{T+2}\dots$ describe a flow of differences. Malloy, Jensen and Song (2005) use a small Boolean system, 4-Node Standard, as an example. The landscape generated by this small system contains three basins. The attractor for Basin 1 is described by the repeating sequence of the following state vectors: $\{\{1001\}, \{1011\}, \{1111\}, \{1101\}\}$, along with five tributary vectors leading into one or another state vector in the attractor. (Note that that sequence of attractor vectors can be arranged in rows to create an attractor matrix which facilitates computational analysis.) Basin 2 consisted of an attractor cycle defined by the sequence $\{\{0001\}, \{1100\}, \{1100\}, \{1000\}\}$ along with two tributary state vectors. Basin 3 contained a single state vector, $\{0000\}$, which cycles directly back onto itself thus defining a point attractor. Basin 3 had no tributaries. An NK Boolean network generates N^2 state vectors; thus the 16 state vectors listed above describe this system's full landscape.

Malloy, Jensen and Song (2005) described TAO-1, a discrete analogue of the first derivative, which is an analytic tool based on the XOR operator and is used to find differences among differences. In logical terms, the XOR operator returns a 1 if either p is true or q is true (but not if both are true); it returns a 0 if both p and q are true or if both p and q are false. Another way to say this is that XOR detects difference; it returns a 1 if p and q are different and a 0 if they are the same. The use of XOR in the TAO (derivative) operation is to detect change for each node from one iteration to the next iteration. Suppose, in a 4-node system (see 4-Node Standard in Malloy, Jensen & Song, 2005), we have two state vectors (each showing the state of each of the four nodes in order) $S_{T=1} = \{1001\}$ and $S_{T=2} = \{1101\}$. Using XOR to compare each respective position of these two vectors across time, TAO-1 returns a vector of differences in differences (across time) **TAO-1** = $\{0100\}$ because from $T=1$ to $T=2$ only the state of the second node is different.

In this paper we explore the utility of extending this logic to TAO-2, TAO-3, and so on (this is analogous to taking higher order derivatives). The point of this extension is to model Bateson's proposal that there is a hierarchy of differences in differences in knowledge. TAO-2 is generated by recursively applying the XOR operator to the output vectors of TAO-1. This is the first step in specifying, in terms of a Boolean model, the hierarchy of differences suggested by Bateson. These higher-order derivatives will be described here as general analytic tools for exploring patterns in the flow of changes in NK Boolean systems. These calculations are performed by software called E42.

Table 1			
Recursive application of TAO to the attractor cycle of Basin 1			
Process	Level-1 Abstraction	Level-2 Abstraction	Level-3 Abstraction
Flow of Differences	Differences in {Differences}	Differences in {Differences in Differences}	Differences in {Differences in Differences }
Original State Vector	TAO-1	TAO-2	TAO-3
T=1	{1001}		
T=2	{1101}	2 vs 1 {0100}	
T=3	{1111}	3 vs 2 {0010}	(3 vs 2) vs (2 vs 1) {0110}
T=4	{1011}	4 vs 3 {0100}	(4 vs 3) vs (3 vs 2) {0110}
		1 vs 4 {0010}	(1 vs 4) vs (4 vs 3) {0110}
			(2 vs 1) vs (1 vs 4) {0110}
			[(4 vs 3) vs (3 vs 2)] vs [(3 vs 2) vs (2 vs 1)] {0000}
			[(1 vs 4) vs (4 vs 3)] vs [(3 vs 2) vs (2 vs 1)] {0000}
			[(2 vs 1) vs (1 vs 4)] vs [(1 vs 4) vs (4 vs 3)] {0000}
			[(3 vs 2) vs (2 vs 1)] vs [(2 vs 1) vs (1 vs 4)] {0000}

Examine the first column of Table 1 (based on 4-Node Standard, Malloy, Jensen & Song, 2005) which shows the four vectors of an attractor cycle of one basin. Note that these vectors occur one after another deterministically in the dynamics of a small, four-node system and that, since they represent dynamics of an attractor cycle, that the top state vector {1001} in Table 1 will occur again immediately after the last (bottom) state vector {1011}. To fully code the four vectors of that attractor cycle we would have a matrix whose rows would be the four vectors. In general, for a system with N nodes that has fallen into an attractor of length, L, iterations, the attractor dynamics would be captured in an NxL matrix.

The second column (TAO-1) summarizes the comparisons made by TAO-1 (i.e., by the XOR function) between successive state vectors in column 1. At this point the reader should be able to confirm those vectors. Column 2 lists the TAO-1 vectors: [{0100}, {0010}, {0100}, {0010}] which together could be expressed more properly as a TAO-1 as an NxL matrix (here both N and L are four). Notice that, whereas in column 1 there are four distinct patterns of differences exhibited in the state vectors of basin 1, the pattern of differences in the output of TAO-1 (second column) is less rich, exhibiting only

two distinct vectors, {0100} or {0010}, among the four vectors listed. In a similar way to the above process, TAO-2 (column three) is the application of the XOR operator to the output of TAO-1. The XOR operator generates the vectors shown in the third column (TAO-2) by comparing successive vectors listed in the second column and outputting a 1 for each node that is different and a 0 for each node that is the same.

Notice that in the TAO-2 column the pattern of differences is even less rich than it was in the TAO-1 column; in fact there is only one pattern of differences, {0110}, among the four TAO-2 output vectors. The reader should be able to confirm these results directly. Finally, in the fourth column, TAO-3 examines the differences among the (TAO-2) differences. Since all the vectors are identical in the TAO-3 column there are no differences in TAO-2 outputs. Therefore all TAO-3 vectors = 0. At any stage of recursive application, the total TAO ensemble of vectors is, of course, a TAO matrix. Table 1 demonstrates E42's functional operations onto which we are mapping Bateson's verbal descriptions of taking differences in differences. How this leads to a hierarchy of differences is implicit in Table 1 and will be developed below.

Methodologically, it should be noted that Malloy, Jensen and Song (2005) also describe how E42 is able to detect attractor cycles; and, when it does so, to place an attractor matrix specifying the dynamics of that attractor in an archive. It then perturbs itself by pseudo-randomly changing the state of fifty percent of its nodes and monitors its own flow until (if) it detects another attractor cycle. E42 continues the previous three steps until it reaches a user-specified number of self-perturbations. Thus it constructs an archive of attractor cycles, often with hundreds or thousands of attractor matrices. As we will detail below, it then can take whatever derivative, say TAO-2, and sort all attractors that have the same TAO-2 matrix into a single category. What we find is that at some TAO level, say TAO-2, there will be many categories of attractors; within each category the attractors all have identical derivatives; between categories the derivatives are different. Thus E42 can generate sets of categories at TAO-1, TAO-2, TAO-3, etc. After summarizing how attractor cycles are visualized, we will return to examine how the categories at different TAO levels form a hierarchy.

Visualizing Basins

Rotate the state vectors in Table 1 to be column vectors; then put these column vectors on a grid with 0's represented as white cells and 1's represented as black cells. Figure 1a shows the original state vectors of attractor cycle detailed in Table 1. The system has 4 nodes (ordinate); sixteen iterations are shown on the abscissa. Black cells represent a 1 in a columnar state vector while white cells represent a 0. Since the length of the attractor cycle is four iterations, Figure 1a shows four passes through the attractor cycle. The reason for showing four cycles is to take advantage of the strong, recognizable patterns resulting from perceptual tiling; each pass through the attractor creates a tile and four tiles together produce the kind of pattern that will be hierarchically categorized below. Figure 1b visually represents the TAO matrices derived in Table 1. Note that the patterns inherent in the TAO derivatives will not be categorized below; rather the TAO's will be the basis of the categorical sorting of the attractor cycle patterns.

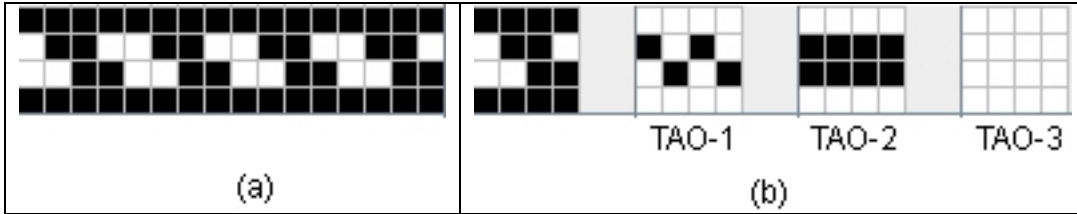


Figure 1. Attractor dynamics for Basin 1. Nodes are on ordinate and iterations on abscissa. Visualized dynamics replace Boolean 0's with white cells and 1's with black cells in matrices. (a) Sixteen iterations (four passes through the attractor cycle of length $L=4$ iterations). Showing four passes through an attractor produces a strong visual pattern due to perceptual tiling effects. (b) The $N \times L$ attractor cycle matrix along with its $N \times L$ matrices for the first three derivatives.

Figure 2 shows the dynamics of the attractor cycle for Basin 2 along with its first three TAO derivatives. In Figure 2a notice that the visualized dynamics of this second attractor cycle produce a distinct pattern from that of the attractor in Figure 1a. While it is not shown in Figure 2b, it should be obvious that TAO-4 would be the $\mathbf{0}$ matrix (all white cells). A mathematical and theoretical treatment of the interesting result that the TAO-1 pattern for attractor 2 (shown in Figure 2b) is identical to the attractor 1 pattern shown in Figure 1b is both lengthy and a tangent to the focus of this paper; the fact that one attractor's derivative can be another attractor in a landscape has interesting epistemological implications and can be explained in terms of the symmetries, broken symmetries, and symmetry groups inherent in a Boolean landscape (Malloy, Butner, Cooper, Smith & Dickerson, 2007).

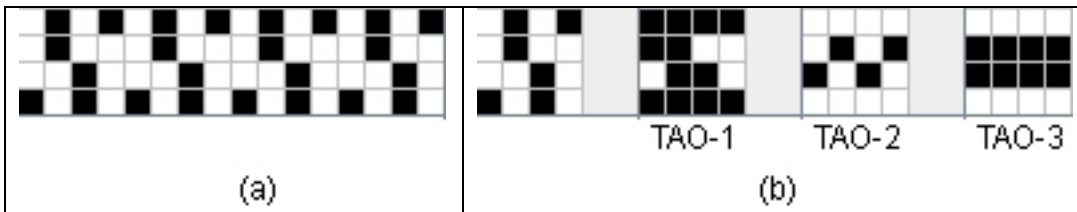


Figure 2. Attractor dynamics for Basin 2. (a) Sixteen iterations (four passes through the attractor cycle of length $L=4$ iterations). (b) The $N \times L$ attractor cycle matrix along with its $N \times L$ matrices for the first three derivatives.

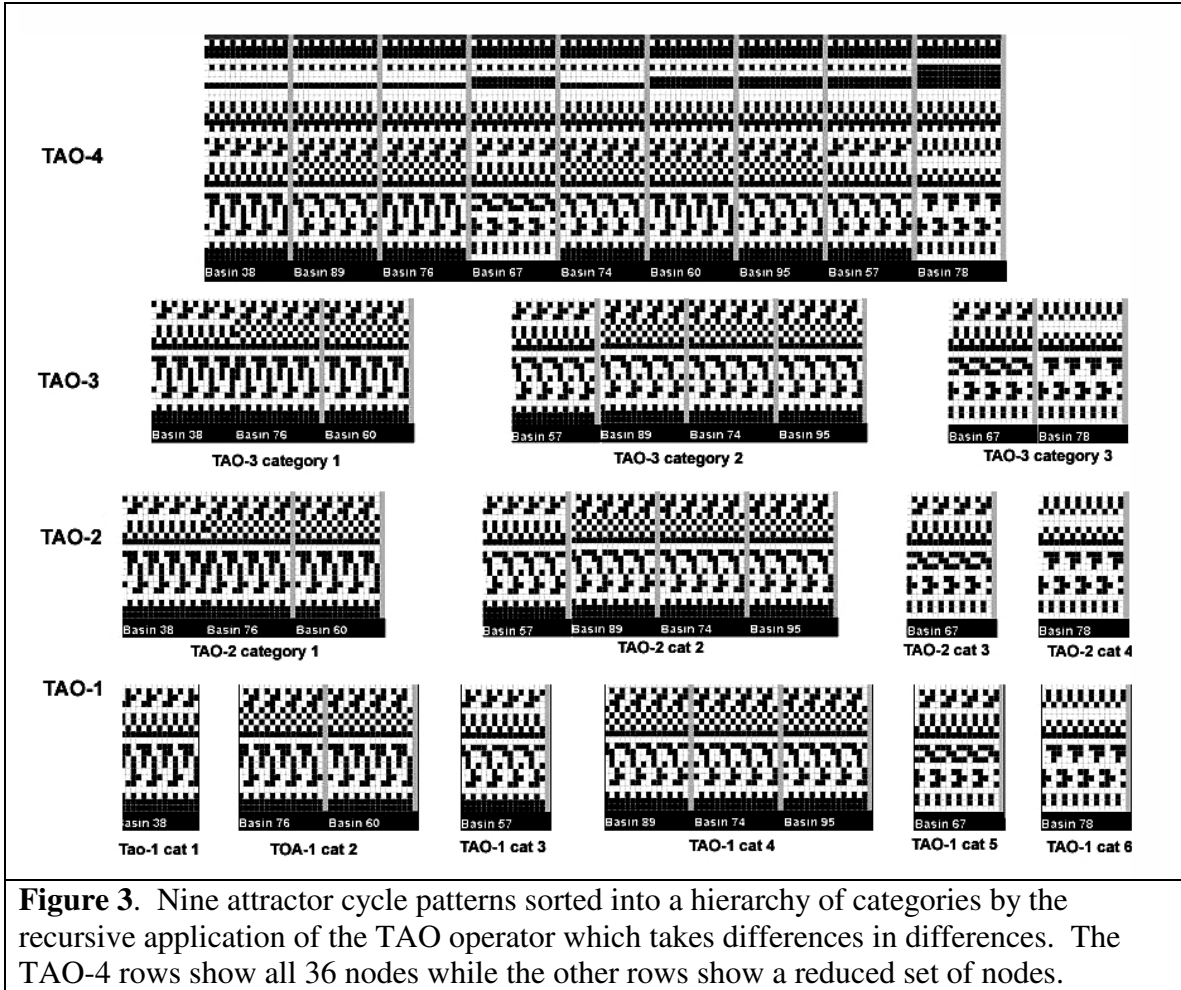
MAPPING PERCEPTUAL EXPERIENCE TO DIFFERENCES IN DIFFERENCES

Hierarchical Perceptual Categories based on Dynamic Constancy

Let us return to the patterns of differences in differences generated by the recursive application of the TAO operator and apparent in Table 1. 4-Node Standard gives us a sense that the variability in the attractor pattern becomes simpler as TAO is recursively applied. But 4-Node Standard is too simple for another crucial insight which is that different attractor patterns can have identical TAO matrices. Since TAO matrices describe the changes in the flow of change, identical TAO matrices means that there are

constancies in the dynamics of the flow. How shall we relate these kinds of dynamic constancies, which are a formal characteristic of the model, to Bateson's proposal that an essential characteristic of knowing is a hierarchy of differences in differences? We require a more complex system than 4-Node Standard to explore that mapping fully.

Figure 3 is based on another NK Boolean system with $N=36$ nodes and shows nine attractor cycles of length $L = 4$ iterations from that system represented as visual patterns. The top row (TAO-4) of Figure 3 shows the 36 nodes on the vertical axis and sixteen iterations (for each attractor) on the horizontal axis; thus each attractor pattern of $L=4$ is shown repeating itself 4 times. In Figure 3 these nine attractor patterns are placed into categories in four different ways (bottom row through top row). The rows of Figure 3 are labeled TAO-1, at the bottom, to TAO-4, at the top. It is important to note that Figure 3 shows only representations of attractor cycle matrices; it does not show representations of TAO matrices. While TAO vectors are never themselves represented they are the basis of the sorting of attractor patterns in each of the four rows. One final note on the presentation in Figure 2: Only the top row (TAO-4) of Figure 3 shows the visual patterns for all 36 nodes. The other three rows (TAO's 3, 2, and 1) are reduced; they cut off the top nodes and show only the bottom 21 nodes. The reason is to reduce the size of the figure for printing and to focus on the perceptually interesting parts of the patterns. The full patterns are available to the reader in the top row and it is these nine full patterns that are in fact being sorted in the lower rows. The reduced set of nodes makes perceptual processing simpler. The top 15 nodes (shown in the TAO-4 row of Figure 2) are necessary to distinguish basins 89, 74, 95 from each other and to distinguish basins 76 and 60 from each other.



In the bottom row of Figure 3 the nine attractor patterns are sorted by TAO-1 matrix identity. For example, the three basins (basins 89, 74, and 95) in TAO-1 category 4 all have identical TAO-1 matrices. Similarly, the two attractor patterns in TAO-1 category 2 (basins 76 and 60) share identical TAO-1 matrices. The rest of the attractors shown in the TAO-1 row are singletons; for the singletons none of the nine basin patterns share the same TAO-1 matrix. The idea is that all attractor cycle patterns that are in the same category share a constant pattern in their flow of change at the level of TAO-1. Another way to say this is that the changes in differences over time are constant for all basin patterns in the same category. We call this Dynamic Constancy and it is proposed here to be a principle for the construction of hierarchies within the model that map to human perceptual experience.

Let us examine higher order dynamic constancies. Examine the second row, TAO-2, in Figure 2. When we use the equality of TAO-2 matrices the patterns are sorted into four categories. This means that the three basin patterns in TAO-2 category 1 (basins 38, 76 and 60) all have identical TAO-2 matrices. Thus basin 38 is now in the same category at the TAO-2 level as are basins 76 and 60, whereas it was in a distinct category at the TAO-1 level. Basin 38 shares second order dynamic constancies with 76 and 60. To emphasize, at each level of this hierarchy the same nine basin patterns are shown, just

sorted differently. TAO matrices are nowhere represented; they are the criteria by which the basin patterns are sorted. Based on identity of TAO-2 matrices, we can see in the TAO-2 row of Figure 3 that the nine patterns can be sorted into four categories.

In contrast to the four categories generated by TAO-2 matrix identity, TAO-3 matrix identity sorts the nine patterns into three categories (second row from top of Figure 2). For example, TAO-3 category 3 is defined by attractor cycles that all have identical TAO-3 matrices (basins 67 and 78). Notice that perceptually basins 67 and 78 are somewhat unlike each other; the characteristic by which they are placed together is a higher level of abstraction. It is metaphorically akin to placing both geese and blue jays in class aves; they do not greatly resemble each other but have abstract characteristics in common. The TAO-4 vector (fourth derivative) is identical for all nine patterns; therefore they are placed in the same category by TAO-4 (see top row of Figure 2). You are asked to look at the hierarchy of categories and check them against your own perceptual experience. Note that the same nine patterns are repeated at each level but are categorized differently. Are these perceptually plausible ways of sorting the patterns? If so, at what level? Note that in biological taxonomy a particular person may or may not sort life forms spontaneously as the taxonomy does; the question is after a person knows the taxonomy does the sorting make sense? Many people categorize the forms in categories with the same result as either the TAO-1 or the TAO-2 operations. Even if you didn't categorize them in exactly the same way as E42 did, do the TAO categories appear perceptually plausible? If you did categorize the visual forms differently (from either TAO-1 or TAO-2 or TAO-3) what are the differences? As with Gestalt perceptual laws, human visual perceptual experience is taken as the reference point for evaluating the epistemological utility of the model-generated hierarchy in Figures 2. Readers are left to categorize the visual forms and compare them to the model-generated categories. Leaving readers to their own experience (as opposed, say, to a statistical analysis of performance measures of groups of humans) is deeply motivated by epistemological frames (see Malloy, Bostic St Clair, & Grinder, 2005, pp. 105, 113) that place human judgment as the reference point for fields where the patterning being studied is that of humans.

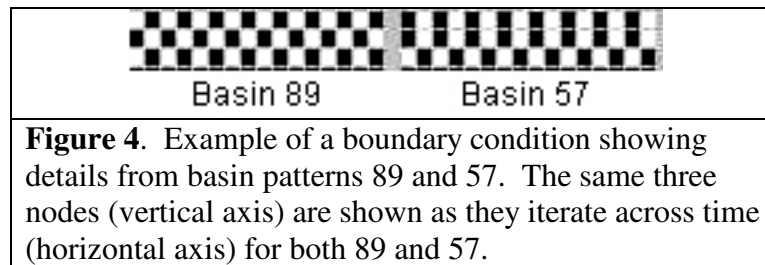
The major results indicate that, first, finding constancies in the flow of differences sorts visual forms into categories and, second, higher-order constancies in the dynamics generate a hierarchy of such categories. As a side note, at a lower level of analysis, the visual forms themselves are generated by finding the dynamic constancy implicit in a system when its flow falls into an attractor cycle.

Boundary Conditions.

The emergence of the kind of perceptual hierarchy seen here is subject to two broad boundary conditions. The first is that such hierarchies exist only for attractor cycle lengths that are powers of two ($L=2, 4, 8, 16, \dots$). While we do find categories at TAO-1 for cycle lengths not equal to a power of 2 they are exactly the same as the categories based on TAO-2 or TAO-3 or higher. There are perceptual categories but no hierarchies. If the attractor cycle length (L) is not a power of 2, we find other interesting results—the higher-order TAO's, rather than diminishing to the $\mathbf{0}$ matrix, as they did with L equal to a power of 2, instead start repeating themselves in complex loops. The theoretical rationale for this boundary condition is based on work with other collaborators and is rather extensive so it is beyond the scope of this paper. Interested parties can request a copy of

ongoing work (Cooper, Butner, Malloy, & Drew, 2007) from the first author; very briefly we can mention that this boundary condition is based on the fractal nature of the XOR operator (Wolfram, 2002, Rule 90) which therefore imbues the TAO discrete derivative operation with fractal properties.

The second boundary condition derives from the fact that perceptual similarity based on TAO matrix identity (dynamic constancy) is best likened to a Gestalt perceptual law. Gestalt perceptual principles are *ceteris paribus* (all things being equal) principles; so too is the principle of Dynamic Constancy described here. All Gestalt principles potentially interfere with each other and, indeed, it is possible to produce examples in which the Gestalt laws of proximity and closure as well as figure-ground relations overwhelm Dynamic Constancy (TAO identity) in human perception. The reader should be able to derive that the TAO-1 matrix for that subset of three nodes shown in Figure 4 is identical for both basin 89 and basin 57: TAO-1 will yield a series of $\underline{1}$ vectors since every node changes on every iteration in both basins.



Therefore, for these particular three nodes, the TAO-1's are identical but, due to Gestalt organization, these details of the visual patterns do not look perceptually similar as predicted by dynamic constancy. Rather they look very different to humans. Checkerboards and columns are perceptually distinct visual organizations even though, dynamically, their rows change in the same way and at the same frequency.

Dynamic Constancy

This study examined Bateson's hypothesis (refer to his mental experiment above) that a key epistemological process is taking differences in differences using a formal nonlinear dynamic systems model which allowed us to characterize the difference taking process with enough specificity to propose a new principle of perceptual organization: Dynamic Constancy. The crucial results are (1) that constancies in the dynamics of the flow of differences in the model define perceptually comprehensible categories of visual forms and (2) that higher-order constancies arrange these categories into a perceptually comprehensible hierarchy. Dynamic Constancy has an advantage over global Gestalt laws in that the process by which it works is computationally well specified in a nonlinear dynamical model. Thus the theoretical traction available in nonlinear dynamic systems theory can be brought to bear upon the further study of perceptual hierarchies.

Limitations and Future Work

Our current goal is rather different than many computational modeling projects. Bateson distinguished between the map (knowledge) and the territory (what is known).

He proposed (2000, p. 457) that that which gets onto the dynamics of maps from the dynamics of the territory are flows of differences and that knowing is a process of finding the dynamical patterns in these flows of difference. Thus defined, knowing and learning were applied very broadly for him:

“I was laying down very elemental ideas about *epistemology*..., that is, about *how we can know anything*. In the pronoun *we*, I of course included the starfish and the redwood forest, the segmenting egg, and the Senate of the United States. And in the *anything* which these creatures variously know, I included 'how to grow into five-way symmetry,' 'how to survive a forest fire,' 'how to grow and still stay the same shape,' 'how to learn,' 'how to write a constitution,' 'how to invent and drive a car,' 'how to count to seven,' and so on... Above all, I included 'how to evolve' because it seemed to me that both evolution and learning must fit the same formal regularities or so-called laws...” (Bateson, 2002, p.4)

While not everyone finds Bateson’s framework useful, we, among others, do. Thus our computational goal is to modernize and to extend the insights of Bateson’s ecological epistemology using the formal insights available from nonlinear dynamical systems. The use of Kauffman’s model (1993) is natural both because the Boolean number base easily maps onto the verbal idea of difference and because Bateson included evolution as a mental process so that Kauffman’s evolutionary insights about the self-organization of evolutionary process aptly map to mental process and learning. That said, our goal immediately defines limitations in our approach. We use the XOR operator to map onto the process of finding differences in the flow of differences. But the XOR operator is known to have computational limitations (e.g., Rumelhart, Hinton, & Williams, 1986) for parallel distributed processing and neural network models. Thus our computational model is rather simple and unlayered compared to many models of learning; in fact, at this stage, E42 is not designed for adaptive learning. Rather it is a descriptive update of the dynamics implicit in Bateson’s ecological epistemology.

This descriptive update is work in process. We are currently defining the nature of the landscape of mental process (modeled as a flow of Boolean differences) to explore the implications of construing knowing as a symmetry breaking process based on the fractal nature of finding, as we do, patterns within a flow of differences. Thus the model, while lacking many of the penetrating insights of other computational models, does address the broad epistemological issues raised by Bateson.

In this study the model generated visual patterns based on the level of abstraction described in the above paragraph; thus the visual patterns shown here do not resemble everyday objects. Dynamic Constancy, therefore, has been demonstrated in these abstract cases but the issue of generalization to everyday objects is still open. This is not unique to Dynamic Constancy. Gestalt Proximity, for example, is typically demonstrated with patterns consisting of rows and columns of simple black objects on a white background. These objects are arrayed different distances apart to demonstrate proximity effects; such arrays do not resemble everyday objects. One possible future direction of inquiry is to use Dynamic Constancy as a theoretical base for creating tools to find the dynamic constancies of digitally scanned everyday objects to examine whether these constancies still produce perceptual categories.

Dynamic Constancy is an outcome of a translation of Bateson’s verbal proposals about the nature of knowledge into a nonlinear dynamic systems model. The conceptual leverage of a well-specified model has refined and extended the Batesonian epistemology in a way that allows us to propose a new principle of perceptual organization, including, within certain boundary conditions, the emergence of perceptual hierarchies.

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