

On Creativity and Elementary Cellular Automata

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Cell-state transition rules of elementary cellular automata (ECAs) are mapped onto the phase space of cognitive control versus schizotypy and CA behavior is interpreted in terms of creativity. To implement the mapping, a definition of creativity proposed by Kuszewski in [1] is quantified by drawing analogies between a degree of schizotypy and the generative diversity of ECA rules, and between cognitive control and robustness of ECA rules (expressed via the Derrida coefficient). It is found that null and fixed-point ECA rules lie in the autistic domain and chaotic rules are schizophrenic. There are no highly articulated creative ECA rules. It is found that two-cycle rules exhibiting wave-like patterns in the space-time evolution are closest to the creativity domains.

1. Introduction: On Creativity

Creativity is a ubiquitous yet elusive concept. Everyone knows what it means to be creative, for example, to be successful in solving problems and generating novel thoughts [2], but few can define creativity rigorously. Substantial progress has been achieved in the fields of computational and psychological creativity. Thus, Kowalik, Dorin, Korb, and McCormack studied the creativity of generating graph patterns and progressed toward outlining creativity as based on a probability of pattern emergence [3, 4]. In this sense, a system is creative if it produces a pattern where the likelihood of emergence is small. Wiggins formalizes Boden's [5] concept of exploratory creativity as the exploration of a conceptual space in [6]. A question could be raised, is creativity in the complexity of conceptual space or the search engine? Other computational approaches to creativity are the generation of novelty via conceptual blending [7, 8] and using analog machines in the evolutionary creation of cross-domain analogies [9].

From a psychological and neurophysiological perspective there is a great similarity between creativity and psychoticism [10–13]. The similarities include an over-inclusive cognitive style, conceptual expansion, associative thinking, and lateral thinking dominating vertical (goal-oriented) thinking. In contrast to creativity, however, psychoticism shows diminished practicality [12, 13]. Kuszewski [1] provides these plausible and psychologically feasible indicators of creativity.

- Divergent thinking and lack of lateral inhibition.
- The ability to make remote associations between ideas and concepts.
- The ability to switch back and forth between conventional and unconventional ideations (flexibility in thinking).
- The generation of novel ideas appropriate for actualities.
- The willingness to take risks.
- Functional nonconformity.

Cognitive control of divergent thinking is a guarantee of creativity. A person with extremely divergent thinking who is unable to control it will be a “nutter.” Those who can fit their high schizotypy traits into a rigid cognitive frame are inclined to genius. Thus, creativity could be positioned together with autism and schizophrenia in the same “phase” space as depicted in Figure 1.

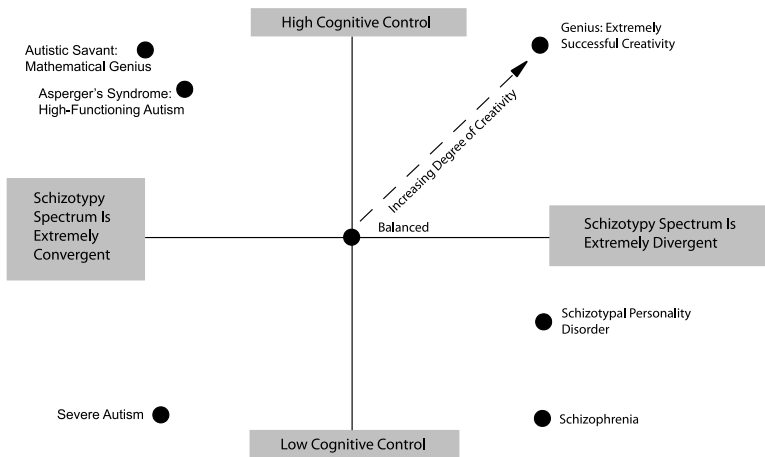


Figure 1. Schizotypy versus cognitive control spaces. Original scheme redrawn from Kuszewski [1].

To develop analogies of Kuszewski’s scheme with cellular automata (CAs), we assume that a cell neighborhood configuration of a CA represents a “thought” or some other elementary quantity of a mental

process, and that a degree of schizotypy is proportional to the diversity of global configurations generated by the CA. We can speculate that cognitive control is equivalent to the robustness of CA evolution. A CA is robust if the trajectory of a disturbed automaton, with some cell states changed externally, does not deviate too far from the trajectory of an undisturbed automaton in terms of Hamming distance. The degree of deviation caused by a disturbance is measured by the Derrida coefficient.

2. Elementary Cellular Automata

An elementary cellular automaton (ECA) is a one-dimensional array of finite-state automata. The automata take two states, 0 and 1, and update their states simultaneously in discrete time by the same cell-state transition function $f: \{0, 1\}^3 \rightarrow \{0, 1\}$. Each automaton updates its state depending on its current state and the states of its two closest neighbors. When referring to cell-state transition rules we use a decimal representation of the cell-state transition table [14]. ECAs have proved to be minimal yet powerfully expressive models of physical, chemical, and engineering systems [15]. For example, they are used in modeling vehicular traffic [16], interactions between discrete solitons [17], complexity of spatially extended dynamical systems [18], pattern formation [19], emergence of chaotic behavior [20], and universal computation [21].

There are $2^{3^2} = 256$ ECA rules. See examples in [22] and extensive analysis of ECA rules, parameters, and global transition graphs in [23]. Due to symmetries, the elementary transition rules can be grouped into 88 classes of equivalent behavior [23, 24]. We analyze them and illustrate our discussions with the minimal decimal value rules from each equivalence class. The rules are studied using two statistical measures: the Derrida coefficient and generative morphological diversity.

The Derrida plot [25] is used in the evaluation of Boolean networks [23, 26–28]. The Derrida plot provides a statistical measure of the divergence/convergence of network dynamics in terms of Hamming distance H . The distance H between two binary states of equal size n is the number of sites that differ. The normalized Hamming distance is H/n . The Derrida plot is calculated as described in [28]. We randomly select a pair of initial states c_1^0 and c_2^0 separated by a small Hamming distance of H_0 at time step $t = 0$. We iterate the configurations using the same cell-state transition rule for m steps and measure H between configurations c_1^m and c_2^m , repeat the measurement, sam-

pling more pairs of initial configurations with the same H_0 , and then plot the normalized H_0 against the mean normalized value of H . The procedure is repeated for larger values of H_0 .

The Derrida coefficient [28, 29], analogous to the Lyapunov exponent but used for discrete systems, measures sensitivity to initial conditions. The Derrida coefficient is derived from the initial slope x of the Derrida plot. For these results $m = 1$. Initially $H_0 = 1$ and it is increased by 1 for 10 samples of 3000. The Derrida coefficient is calculated as $D = \log_2(\tan(x))$. Boolean networks and CAs behaving “chaotically” have positive D ; ordered dynamics have negative D . For Boolean networks $D = 0$ is attributed to dynamics at the edge of order and chaos [27], whereas for CAs $D = 0$ merely indicates stability. Although there might be a closed-form probability expression for the Derrida coefficients for ECAs, for the moment we will measure it numerically/statistically from their Derrida plots.

We equate ECA sensitivity as an analogy to the degree of cognitive control; that is, an individual is able “to maintain a working knowledge of information in their consciousness that is readily available for mental evaluation” and has the “ability to switch back and forth between attentional sets” [1]. In robust ECAs, with a low degree of sensitivity and a high degree of robustness, a perturbation does not propagate far along the ECA space-time configurations. This is a phenomenological equivalent of a latent inhibition—one of the key mechanisms of cognitive control—that prevents over-inclusive thinking [1].

Generative morphological diversity μ of an ECA characterizes how many different triplets of neighborhood configurations, taken at time steps $t - 1$, t , and $t + 1$, are generated by the ECA starting from a single central cell in a state 1 [30, 31]. The measure is very close to the in-degree histogram proposed in [32]. We have chosen 3×3 cell blocks to characterize the morphology of space-time configuration because a minimal block must include a cell neighborhood (three cells), at least two subsequent local configurations (to characterize identifiability), and sides corresponding to time and space with the same number of cells. We calculate the morphological diversity μ using blocks of neighborhood states taken at three subsequent time steps. The diversity is calculated as follows. An automaton is evolved for m steps and a list L of different 3×3 blocks from its space-time configuration $c \times T$ is filled. Step m is the iteration when list L is stabilized; that is, no new 3×3 blocks are added: $L^m = L^{m-1}$. The diversity $\mu = |L|$ is the size of list L .

We equate ECA morphological diversity as an analogy of an indicator of high/low functioning of a prefrontal cortex, which is manifested in a “spectrum of schizotypy ranging from highly creative to schizophrenia” [1].

Values of μ and D for representative rules of equivalence classes are shown in Appendix A.

3. Creativity of Elementary Cellular Automata Rules

Representative rules of the 88 equivalence classes are mapped onto the plane of generative diversity μ versus Derrida coefficient D (μ - D space) in Figure 2. Space-time configurations, starting in configuration 0 ... 010 ... 0, generated by the rules from Figure 2 are shown in Figure 3. A substantial number of rules occupy a domain with low values of μ yet spread more or less equally along the D axis. Rules showing moderate generative diversity ($\mu = 20$ to 40) have Derrida coefficients around $D = 1$. Rules with the highest generative diversity ($\mu = 50$ to 64) have values of D ranging from nearly 1 to 1.6 (Figure 2). The increase in generative diversity is visualized in sample configurations of representative rules (Figure 3).

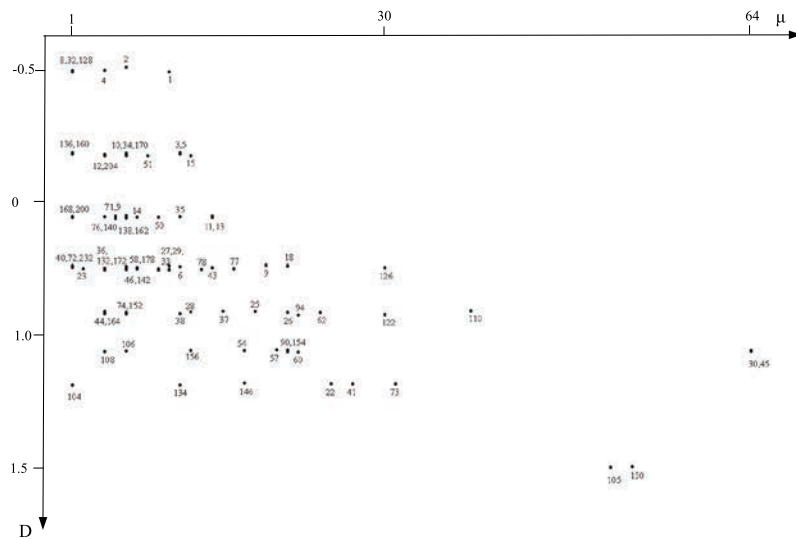


Figure 2. Representative rules of 88 classes are displayed in μ - D space.

Domains of ECA behavioral classes [33] are shown in Figure 4. Fixed-point and two-cycle classes [34, 35] lie in the region of low generative diversity yet fully spread along the Derrida coefficient axis. Rules with periodic behavior occupy a part of μ - D space for average values of generative diversity and Derrida coefficient equal to 1. Chaotic rules are spread from moderate to maximum values of diversity and Derrida coefficient from 0.5 to 1.5. Two complex rules reside in a region of μ equal to 1 and slightly above average diversity μ .

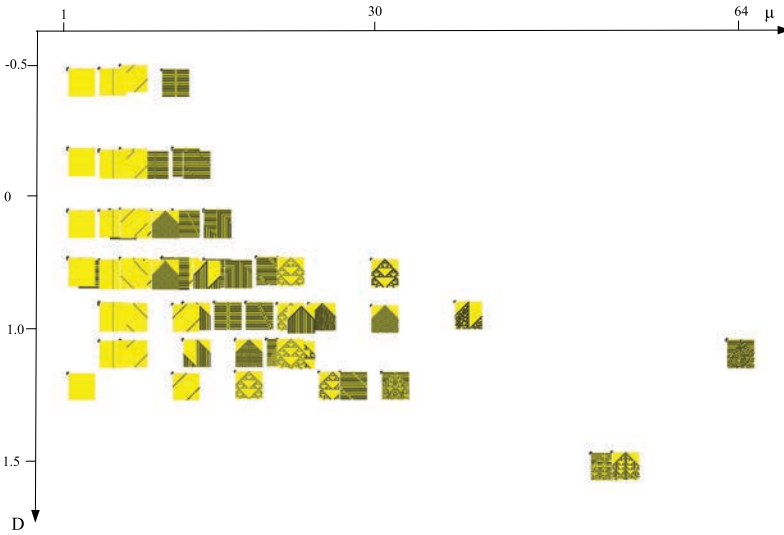


Figure 3. Space-time configurations of representative rules of 88 classes are displayed in μ - D space. Each automaton with 150 cells started its development in a configuration where all cells but one are in state 0 and evolved for 150 iterations. Boundaries are periodic. Cells in state 1 are shown by black pixels; cells in state 0 are yellow.

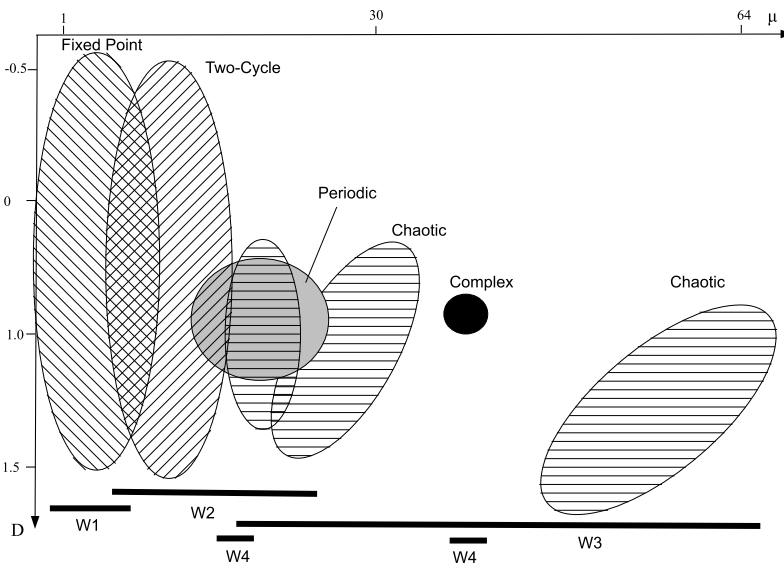


Figure 4. Domains of main behavioral classes [33] in μ - D space. Projections of domains onto Wolfram classes [34, 35] W1 to W4 are shown as solid, thick lines.

Wolfram classes [34, 35] W1 (fixed point), W2 (periodic), W3 (chaotic), and W4 (complex) are well arranged along the generative diversity axis, except for class W4. One rule of class W4 lies in the middle of class W3, and another rule of class W4 lies in the intersection of classes W2 and W3 (Figure 4).

From the distribution of rules (Figure 2) and domains of behavioral classes (Figure 4), we can speculate that—overall—the increase in behavioral complexity, as measured by generative diversity, leads to a decrease in robustness and an increase in sensitivity to initial conditions, as measured by the Derrida coefficient.

Ideally, highly articulated creative rules would appear in the upper-right corner of the upper-right quadrant of the μ - D plane, but because this corner is almost empty, we settled on rules closest to it. Such rules should have above-average generative morphological diversity, and below-average Derrida coefficients: $\mu > 11$ and $D < 0.53$ (we omitted rule 0 as not posing any interest). The following equivalence classes, labeled by their representative rules, satisfy the creativity condition: 3, 5, 11, 13, 15, and 35. Equivalence classes 3 and 5 show the highest degree of robustness, representing cognitive control, among the creative rules with a yet-lower degree of generative diversity, representing the degree of schizotypy. Equivalence classes 11 and 13 show higher generative diversity yet lower robustness. Example configurations of creative ECA rules are shown in Figure 5. The creative ECAs are characterized by propagating patterns, which strikingly resemble waves of excitation propagating in nonlinear active media. There are physiological correlations (see review in [1]), in that creative individuals show activity in both hemispheres and increased inter-hemispheric transfer.

In the quadrant of low generative diversity and high robustness, we observe a transition from normal ECAs to Asperger's syndrome ECAs to autistic ECAs (Figure 5). Normal rules, that is, those with μ and D values closest to average, show stationary or breathing domains of intermittent coherent patterns. Rules analogous to Asperger's syndrome show configurations densely populated with uniform, solid domains of cells in 1 or 0. ECAs interpreted as autistic evolve to fixed all-1 or all-0 global states.

Chaotic rules populate the quadrant corresponding to schizophrenia and schizotypal personality disorders (Figure 5). The most morphologically diverse and least robust, and thus most "schizophrenic" equivalence classes are 30, 45, 105, and 150. Rule 30 is a typical chaotic rule, even used as a random number generator [36]; when enriched with memory, rule 30 shows pronounced dynamics of gliders with sophisticated interaction patterns [37].

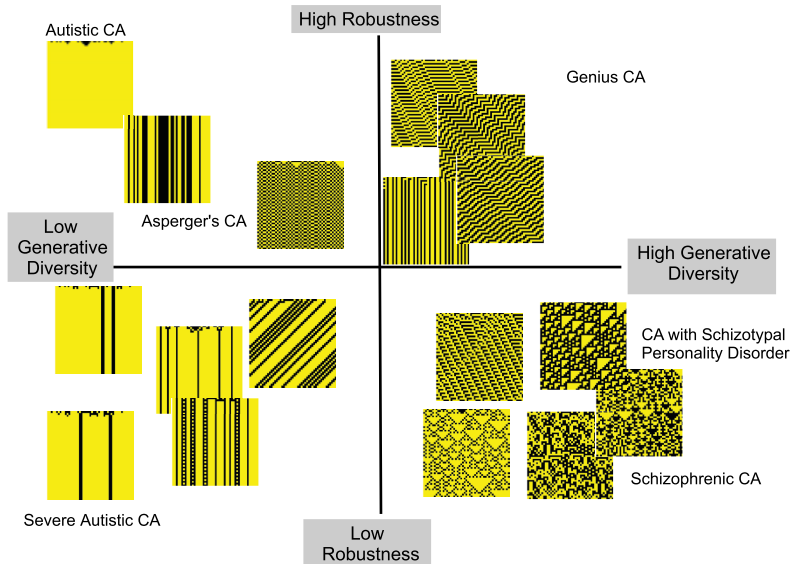


Figure 5. Schizotypy versus cognitive control spaces as seen via generative morphological diversity and robustness (Derrida coefficients), showing an interpretation of Figure 1 in terms of ECA. Examples of space-time configurations generated by autistic, creative, and schizophrenic ECA rules are given. Configurations evolved from initially random uniform distribution of states 0 and 1. Cells in state 1 are black pixels; those in state 0 are yellow pixels.

Autistic ECAs show stationary domains of similar states. There are no propagating patterns in autistic ECAs. The stationary noninteracting domains imitate zones of persistent nervous activity in the brain of a severely autistic person. This could be a possible sign of desynchronization in the motor cortex [38–40].

The dynamics of ECAs governed by schizophrenic rules are characterized by the sudden emergence and subsequent swift collapse of domains of similar states. These are reflected in triangular tessellations visible in the space-time configurations (Figure 5). Assume that a one-dimensional ECA is an abstraction of a brain, and that patterns of 1s are analogous to neurons bursting with excitation spikes. Then, a creative brain produces coherent yet morphologically rich patterns of nervous activity, for example, propagating auto-waves, while a brain with high schizophrenic disorder shows (quasi-) chaotic, incoherent, and “spontaneous” outbursts of nervous activity. These outbursts of activity imitate abnormalities in multiple parts of the brain and diminished temporal stability [41–43].

4. Discussion

Using measures of generative morphological diversity and the Derrida coefficient, we classified elementary cellular automaton (ECA) rules onto a spectrum of autistic, schizophrenic, and creative personality. Four classes are shown in Table 1.

Class	Rules
Creative	3, 5, 11, 13, 15, 35
Schizophrenic	9, 18, 22, 25, 26, 28, 30, 37, 41, 43, 45, 54, 57, 60, 62, 73, 77, 78, 90, 94, 105, 110, 122, 126, 146, 150, 154, 156
Autistic savants	1, 2, 4, 7, 8, 10, 12, 14, 19, 32, 34, 42, 50, 51, 76, 128, 136, 138, 140, 160, 162, 168, 170, 200, 204
Severely autistic	23, 24, 27, 29, 33, 36, 40, 44, 46, 56, 58, 72, 74, 104, 106, 108, 130, 132, 142, 152, 164, 172, 178, 184, 232

Table 1. Four classes of CA creativity.

Autistic rules correspond to rule classes with fixed-point behavior, schizophrenic rules are chaotic, and creative rules belong to a class of two-cycle behavior. There are two types of creativity: creative product and creative process [44]. The creative ECA rules discovered correspond to a creative process; space-time configurations produced by a creative rule may not be creative. Rules 54 and 110 are computationally universal [15, 21, 45, 46], but why are they not creative? Because they lack autonomous cognitive control, defined as robustness in the present paper. These rules perform computation only with strict initial conditions. The computational circuits in these rules do not emerge in their space-time configurations by themselves.

We are aware that this interpretation will appear too simplistic, and that both personality and CAs are profoundly complex. However, we decided to develop this naive conceptual approach to provoke new ways of thinking about and discussing the issues. We also believe that highly articulated creative rules might be found in a richer rule space than ECAs.

It could be that grouping rules into classes of creativity is only valid in the framework of a “cognitive control versus schizotypy” approach [1]. Other definitions of creativity might lead to totally different creative and noncreative groupings. For example, Dorin and collaborators approached uncovering the creativity of dynamic systems by focusing on evaluating the probability of the emergence of rare patterns [3, 4]. With such an approach, ECA rules that produce

traveling localizations, or gliders, with rich dynamics of glider collision outcomes, would likely be classed as the most creative. Computationally universal rules 54 and 110 are noncreative in the framework of our approach. These rules could become creative if we start considering an exploratory creativity [5] and creativity as conceptual blending [7, 8].

Appendix

A. Values of μ and D for Representative Rules of Equivalence Classes

Rule	μ	D	Rule	μ	D	Rule	μ	D
0	1	-inf	35	11	0.307	108	4	0.981
1	10	-0.423	36	4	0.564	110	38	0.778
2	6	-0.446	37	15	0.780	122	30	0.799
3	11	-0.017	38	11	0.792	126	30	0.561
4	4	-0.431	40	1	0.553	128	1	-0.429
5	11	-0.009	41	27	1.145	130	6	0.555
6	11	0.557	42	6	0.313	132	4	0.563
7	5	0.303	43	14	0.561	134	11	1.149
8	1	-0.424	44	4	0.792	136	1	-0.009
9	19	0.550	45	64	0.976	138	6	0.312
10	6	-0.007	46	7	0.567	140	4	0.308
11	14	0.304	50	9	0.309	142	7	0.560
12	4	-0.007	51	8	0.000	146	17	1.140
13	14	0.311	54	17	0.975	150	53	1.562
14	7	0.309	56	6	0.786	152	6	0.793
15	12	0.000	57	20	0.972	154	21	0.974
18	21	0.553	58	9	0.568	156	12	0.975
19	5	0.317	60	22	0.983	160	1	-0.017
22	25	1.143	62	24	0.787	162	6	0.302
23	2	0.566	72	1	0.557	164	4	0.782
24	6	0.567	73	31	1.144	168	1	0.307
25	18	0.782	74	6	0.792	170	6	0.000
26	21	0.786	76	4	0.308	172	4	0.572
27	10	0.573	77	16	0.567	178	9	0.574
28	12	0.783	78	13	0.570	184	6	0.571
29	10	0.569	90	21	0.982	200	1	0.311
30	64	0.980	94	22	0.800	204	4	0.000
32	1	-0.424	104	1	1.150	232	1	0.558
33	10	0.552	105	51	1.564			
34	6	-0.013	106	6	0.979			

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