### OPTIMAL CNN TEMPLATES FOR LINEARLY-SEPARABLE ONE-DIMENSIONAL CELLULAR AUTOMATA P.J. Chang and Bharathwaj Muthuswamy

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### Abstract

In this tutorial, we present optimal Cellular Nonlinear Network (CNN) templates for implementing linearly-separable one-dimensional (1-D) Cellular Automata (CA). From the gallery of CNN templates presented in this paper, one can calculate any of the 256 1-D CA Rules studied by Wolfram using a CNN Universal Machine chip that is several orders of magnitude faster than conventional programming on a digital computer.

## **1** Introduction

The main purpose of this paper is to derive the optimal Cellular Nonlinear Network (CNN) templates for linearly-separable one-dimensional (1-D) Cellular Automata (CA). A gallery of optimal CNN templates for linearly-separable 1-D CA is presented, and an appendix is included to illustrate the template derivation algorithm. These optimal templates may be implemented on any CNN universal chip [Chua & Roska, 2002], thereby allowing faster calculation of any of the 256 1-D CA rules [Wolfram, 2002] by several orders of magnitude. Such great enhancement in speed will enable researchers on CA to conduct extensive simulations over much longer periods (e.g., over many *trillions* of iterations) of Wolfram's class 3 and 4 CA rules than currently feasible.

### A. Truth Tables and Boolean Functions

Boolean Functions are described by truth tables. For the purpose of this paper, the inputs to the truth tables are binary 3-tuples,  $(x_{i-1}, x_i, x_{i+1})$ . That is, each of  $x_{i-1}, x_i, x_{i+1}$  can be either 1 or 0, leading to the generation of  $2^3 = 8$  input combinations, listed in order as (0,0,0), (0,0,1), (0,1,0), (0,1,1), (1,0,0), (1,0,1), (1,1,0), (1,1,1). Each 3-tuple input is mapped to a binary output y that is also either 1 or 0. Thus, there are  $2^8 = 256$  possible truth tables generated from 3 binary inputs. Each of these 256 truth tables corresponds to a unique Boolean Function, which is named as the decimal equivalent of the binary number formed by

concatenating the output of each row in the truth table in reverse order. For example, when mapping (0,0,0) to 0, (0,0,1) to 1, (0,1,0) to 1, (0,1,1) to 1, (1,0,0) to 0, (1,0,1) to 1, (1,1,0) to 1, (1,1,1) to 0, the outputs may be written as the 8-tuple binary code (0,1,1,1,0,1,1,0). Concatenating these outputs in reverse order results in the binary number 01101110, whose decimal equivalent is 110. The corresponding Boolean Function is thus named as 110, which equals  $0 \cdot 2^7 + 1 \cdot 2^6 + 1 \cdot 2^5 + 0 \cdot 2^4 + 1 \cdot 2^3 + 1 \cdot 2^2 + 1 \cdot 2^1 + 0 \cdot 2^0$ . Figure 1 presents that truth table and the derivation of the name.



Figure 1. The derivation of Boolean Function 110 and its truth table

### B. Cellular Automata

A cellular automaton is a collection of cells that iterates on a set of rules, creating a new generation of cells with each iteration. A 1-D CA is a string of cells. It is assumed that the boundary condition is *periodic*, so that the string of cells is effectively a *ring* of cells as illustrated in Figure 2 for the case of a 1-D CA made of 10 cells.



Figure 2. A sample 1-D 10-cell CA initial condition and its periodic boundary condition

The set of rules that govern the cells of the 1-D CA are summarized by 256 3-tuple truth tables. Each truth table is a Boolean Rule that dictates a distinct 1-D CA pattern from a given initial condition. For the purposes of studying 1-D CA, the initial condition would be a string of cells of an arbitrary length greater than or equal to 3 cells. Each cell would indicate a value of "0" or "1". To find the output of each cell of a particular 1-D cellular automaton according to a fixed Boolean Rule, the cell in question is seen as  $x_i$ , its left neighbor as  $x_{i-1}$ , and its right neighbor as  $x_{i+1}$ . The corresponding output  $y_i$  mapped from the resulting ( $x_{i-1}$ ,  $x_i$ ,  $x_{i+1}$ ) in the truth table would be the output of the cell  $x_i$ . For example, let {1,1,0,1} be a sample initial condition bit string of length 4 for a 1-D 4-cell CA, given the truth table of Boolean Function 110, usually dubbed *local Rule 110* in literature. Consider the third cell that contains "0." The left and right neighbor cells are the second and fourth cells, respectively, both containing "1." The output of the third cell would be the output y mapped from the 3-tuple (1,0,1) from the truth table of local Rule 110. According to the truth table, when  $x_{i-1} = 1$ ,  $x_i = 0$ , and  $x_{i+1} = 1$ , the output  $y_i$  is 1, and hence the output of the third cell is "1." The same process is repeated for each cell listed in the initial condition, resulting in the new *evolution* {0,1,1,1}, and

completes one iteration of the 1-D CA. This new evolution,  $\{0,1,1,1\}$  would be the new initial condition for the next iteration. If all the cells containing "1" are colored red, and all the cells containing "0" are colored blue, then a pattern begins to emerge from the evolutions after several iterations. The first iteration for local Rule 110 is derived in Figure 3.



Figure 3. Starting with a sample initial condition, the next generation is found for Boolean Function 110.

In order to discover the distinct 1-D CA pattern generated by a local Rule and given initial condition, one would have to run the CA through several iterations. Some local Rules even have never-ending patterns<sup>1</sup> formed from almost all possible initial conditions, such as Rules 30 (binary code 00011110) and 110 (binary code 01101110), as illustrated by Figure 4, when assuming an infinite number of cells.

<sup>&</sup>lt;sup>1</sup> Even for just 100 cells, there are  $2^{100}$  distinct bit-string patterns.



Figure 4(a). The pattern generated from rule 30 for a random initial condition. Notice how there is no repeated

iteration.



Figure 4(b). The pattern generated from rule 110 for a random initial condition. Notice how there is no

repeated iteration.

A Personal Computer (PC), which only has limited processing speed, certainly will not return these patterns instantaneously, especially if the initial condition bit string increases in length. Investigating higher dimensions of CA also poses future problems in pattern finding with a PC. A CNN universal chip is ideal for automation of n-cell 1-D CA not exceeding the array size of the chip.<sup>2</sup> Thus, a CNN provides a dynamical system that completely predicts the CA evolution for any initial condition. The CNN chip has high processing speed (it can process under 1 nanosecond per iteration!), low power dissipation, and parallel processing. [Chua et al, 2002] All that is needed to program a CNN universal chip to automate the patterngeneration is templates that describe the Boolean Rules. These templates are found from corresponding Boolean Cubes.

#### C. Boolean Cubes

Since the 8 possible outputs in each truth table is either 0 or 1, there are  $2^8 = 256$  possible Boolean Functions/Rules. Each of these 256 Boolean Rules can be represented as a threedimensional Boolean Cube for better visualization and analysis. For the reader's convenience, Table 1 from [Chua et al, 2003] is reprinted herein as Table 1. Note that the Cubes that have numbers labeled in red are *linearly-separable*, while the Cubes that have numbers labeled in blue are *linearly non-separable*; these terms will be clarified in the following Section D. The lower box describes the coloring of the vertices of the Cubes, and how the vertices' coordinates are derived from substituting "-1" for "0" for use in determining an analytical formula. Please refer to Figure 5 in deriving the analytical truth table and hence the coordinates of the vertices.

<sup>&</sup>lt;sup>2</sup> The current commercially available CNN chip has an array size of 176 x 144 [Anafocus, 2007].

		2	3	• •				6 6 6 6 6 6 6	7	
	9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9			0	12 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0			14 •••• •••• 22		<b>1111111111111</b>
		26	27	•		29		30		<b>1111111111111</b>
				•		3'		38 38	39	0 0
	41	42	43	9	44 ••••• 52	4	5	46	47	9
56	57	58	59	9	60	6		62	63	J
N = 0	decimal equivale $P_{4}$ $P_{5}$ $P_{4}$ $2^{2} = 4$ $2^{2}$ $2^{4}$ $2^{4}$ $2^{4}$ $2^{64}$ $6^{(1,1,-1)}$ $2^{6}$ $1$ $0^{(1,1,-1)}$ $2^{6}$ $1$ $0^{(1,1,-1)}$ $2^{6}$ $1$ $1$ $1$ $1$ $1$ $1$ $1$ $1$ $1$ $1$	ent of binary num $p_1, p_2, p_3, p_4, p_5, p_6, p_6, p_6, p_6, p_6, p_6, p_6, p_6$	nber $\beta_0$ $2^2 = 8$ $2^1 = 2 \rightarrow u_{i+1}^4$ Rule N		vertex () () () () () () () () () ()	$u_{i-1}^{t}$ -1 -1 -1 -1 -1 1 1 1 1	$u_i^t$ -1 -1 1 -1 -1 -1 1	$ \begin{array}{c c}  & u_{i+1}^t \\ \hline  & -1 \\ \hline  & -1 \\ \hline  & 1 \\ \hline  & 1 \\ \hline  & -1 \\ \hline  & 1 \\ \hline \hline \hline  & 1 \\ \hline \hline \hline  & 1 \\ \hline \hline$	$ \begin{array}{c}  u_i^{2+1} \\  \hline  \gamma_0 \\  \hline  \gamma_1 \\  \hline  \gamma_2 \\  \hline  \gamma_3 \\  \hline  \gamma_4 \\  \hline  \gamma_5 \\  \hline  \gamma_4 \end{array} $	
₿ →	$= u_i^{t+1}(\mathcal{U}_{i-1}^t, \mathcal{U}_{i-1}^t)$	$u_i^t, u_{i+1}^t) = -1$	$  \beta_k = 0 $	)	0	1	1	1	<i>Y</i> 7	

Table 1. Encoding 256 local rules defining a binary 1D CA onto 256 corresponding "Boolean Cubes" [Chua et. al, 2003].

## Table 1 (continued)

64	65	66	67	0	68	65		70	71	0
<b>72</b>	73	74	75	0-0	76	7		78	79	0
80	81	82	<b>8</b> 3	0-0	<b>8</b> 4	8		86	87	9
88	89	90	91	9	92	9:		94	95	•
<b>96</b>	97	98	99	0	100	10		102	103	•
104	105	106	107	<b>0-0</b>	108	10	9	110		0
	113	114	115	9	116		7	118	119	0
120	121	122	123	000	<b>1</b> 24	12	5	126	127	0
N = 0	lecimal equivale	nt of binary nur	nber		vertex	$u_{i-1}^t$	$u_i^t$	$u_{i+1}^t$	$u_i^{t+1}$	
<i>P</i> 7		▲ui			0	-1	-1	-1	γa	
	(-1,1,-1) $2^2 = 4$	(-1,1,1)3	22 = 8		1	-1	-1	1	γ <sub>1</sub>	
2 <sup>6</sup> =	$2^6 = 64$ <b>6</b> (1,1,-1) (1,1,						1	-1	γ <sub>1</sub>	
	$2^{u} = 1$ $(-1, -1, -1)$ $(-1, -1, -1)$ $(-1, -1, -1)$ $(-1, -1, -1)$						-1	-1	γ.	
24 =	16 4 (1,-1)	(1)1 5 == 2 <sup>5</sup> = 32		6	1	-1	1	γ <sub>1</sub>		
	$\textcircled{B} \longrightarrow u_i^{t+1}(u_{i-1}^t, u_i^t, u_{i+1}^t) = 1 \Longrightarrow \beta_k = 1$						1	-1	Ϋ́ι	
₿ →	$u_{i} (u_{i-1}, u_{i}, u_{i+1}) = 1 \implies \beta_{k} = 1$ $u_{i}^{t+1}(u_{i-1}^{t}, u_{i}^{t}, u_{i+1}^{t}) = -1 \implies \beta_{k} = 0$						1	1	<i>Y</i> 7	

## Table 1 (continued)

128	129			00	132			134	135
	125 000 137		131 <b>9</b> <b>9</b> <b>9</b> <b>9</b> <b>9</b> <b>9</b> <b>9</b> <b>9</b>	9				142	143
<b>1</b> 44	145	146	<b>1</b> 47	0-0	<b>999999999991</b> 48	14	9	150	151
152	153	154	155	•	9 9 9 156		7	158	159
	161	162	163	0	<b>1</b> 64		5	166	<b>1</b> 67
168	169	170	171	9	172	17	3	174	175
176	177	178	179	9	180	18		182	183
184	185	186	187	0	188	18	9	190	191
N = 0	lecimal equivale	ent of binary num $\beta_1$ $\beta_2$ $\beta_1$	nber Ø.		vertex	$u_{i-1}^t$	$u_i^t$	$u_{i+1}^t$	$u_i^{t+1}$
	(-1,1,-1) 2 <sup>2</sup> = 4 <b>2</b>	(-1,1,1) <sub>3</sub>	2 <sup>3</sup> = 8		0	-1	-1	-1	Ϋ <b>σ</b> Ϋ 1
2 <sup>6</sup> =	64 6 (1,1,-1) 2 <sup>0</sup> = 1 0	(1,1,1 y 2 <sup>9</sup> = 128	2'=2 ► u' <sub>i+t</sub>		3	-1 -1	1	-1	γ <sub>1</sub> γ <sub>1</sub>
2 <sup>4</sup> =	16 - 4 (1,-1	(1,1,1,1) $((1,1,1))(1)$ $(1,1,1)(1) (2^{5}=32)$	Rule N		()	1	-1	-1	γ., γ.,
vertex	$u_{i-1}^{t+1}$	$u_{i}^{t} u_{i}^{t} $ = 1	B <sub>1</sub> = 1		0	1	-1	-1	7 3 7 1
₿ →	$u_i^{t+1}(u_{i-1}^t, u_{i-1}^t, u_{i-1}^t,$	$u_i^t, u_{i+1}^t) = -1$	$\implies \beta_k = 0$	)	0	1	1	1	¥ 7

## Table 1 (continued)

192	193	194	195	00	<b>999999991</b> 96	19	7	198	199	0
200	201	202	203	0-0	204	20	5	206	207	
208	209	210	211	000	212	21	3	214	215	9
216	217	218	219	•	220	22		222	223	•
224	225	226	227	0	228	22	9	230	231	•
232	233	234	235	0-0	236	23	7	238	239	0
240	241	242	243	0	244	24	5	246	247	0
248	249	250	251	00	252	25	3	254	255	0
N = c	lecimal equivale	nt of binary nur	nber		vertex	$u_{i-1}^t$	$u_i^t$	$u_{i+1}^t$	$u_i^{t+1}$	
	<u> </u>	▲ui			0	-1	-1	-1	γo	
	(-1,1,-1) 2 <sup>2</sup> = 4 <b></b> 2	(-1,1,1)3	23 = 8		1	-1	-1	1	γ <sub>1</sub>	
2 <sup>6</sup> =	64 6 (1,1,-1)	(1.1.1 <b>y 1</b> 2 <sup>2</sup> = 128		2	-1	1	-1	γ <sub>1</sub>		
	2° = 1 = 0	1,1,1) (1,1,1)	2'=2 uin		0	-1	1	1	γ <sub>1</sub>	
2 <sup>4</sup> =	16 4 (1,-1	.1) 5 === 2 <sup>5</sup> = 32		6	1	-1	-1	<i>Y</i> 1		
vertex	$u_{i-1}^{t+1}$	$u_{i}^{t}$ $u_{i+1}^{t}$ $= 1$		6	1	1	-1	γı		
₿ →	$ \begin{array}{c} & & & u_i^{**}(u_{i-1}^*, u_i^*, u_{i+1}^*) = 1 & \longrightarrow & \beta_k = 1 \\ \hline \\ & & & & u_i^{t+1}(u_{i-1}^t, u_i^t, u_{i+1}^t) = -1 & \longrightarrow & \beta_k = 0 \end{array} $						1	1	<i>Y</i> 7	

To recapitulate, in determining the Cube, if all the symbolic 0 values in the truth tables are replaced as -1 for numerical analytical purposes, then the new input values  $u_{i-1}$ ,  $u_i$ ,  $u_{i+1}$  would be the coordinates of the Cube's vertices, with u = x - 1. The vertices would be colored according to the associated output  $y_i$  such that each Rule is represented as a unique Cube; vertices would be colored blue if the associated output is -1, and vertices would be colored red if the associated output is 1. The corresponding analytic truth table and Boolean Cube for Rule 110 is presented in Figure 5.



Figure 5. Converting symbolic truth table into analytic truth table to derive Boolean Cube. The 8-bit binary string is the binary number whose decimal equivalent is the name of the local Rule.

#### D. Complexity Index

These 256 Boolean Cubes may be categorized according to *complexity*. Each Cube is assigned a *complexity index*  $\kappa$ , which is the minimum number of planes needed to separate red vertices to one side of the plane, and blue vertices to the other. This complexity index is determined by inspection of the color of the 8 vertices in the Boolean Cube. Cubes that have  $\kappa$ = 1 require only 1 plane to separate the red vertices from the blue, and are *linearly-separable*, e.g. the Cube for Rule 16. Cubes that have  $\kappa$ = 2 require 2 planes, such as the Cube for Rule 18, and Cubes that have  $\kappa$ = 3 require 3 planes, such as the Cube for Rule 150, as shown in Figure 6. These Cubes that require more than 1 plane to separate the red and blue vertices are *linearly non-separable*. The highest complexity index possible for the 256 1-D CA Boolean Cubes is 3.



Figure 6. Rule 16 has  $\kappa$ =1, Rule 18 has  $\kappa$ =2, Rule 150 has  $\kappa$ = 3. The 8-bit binary string above each Boolean Cube denotes the binary number whose decimal equivalent is the name of each local Rule.

There are 104 Boolean Cubes that are linearly-separable; the corresponding 104 Boolean Rules are listed in Table 2. Tables 3 and 4 list  $\kappa$ = 2 and  $\kappa$ = 3 Rules respectively. To program a CNN universal chip to generate the pattern associated with a given Rule, templates describing the Rule must be specified as data input of the program automatically by the CNN operating system that comes with the chip.

0	1	2	3	4	5	7	8	10	11	12	13	14
15	16	17	19	21	23	31	32	34	35	42	43	47
48	49	50	51	55	59	63	64	68	69	76	77	79
80	81	84	85	87	93	95	112	113	115	117	119	127
128	136	138	140	142	143	160	162	168	170	171	174	175
176	178	179	186	187	191	192	196	200	204	205	206	207
208	212	213	220	221	223	224	232	234	236	238	239	240
241	242	243	244	245	247	248	250	251	252	253	254	255

Table 2. All 104 Linearly-Separable Rules,  $\kappa = 1$ 

Table 3. All  $\kappa$ = 2 Rules

6	9	18	20	22	24	25	26	28	30	33	36	37
38	40	41	44	45	52	54	56	57	60	61	62	65
66	67	70	72	73	74	75	82	86	88	89	90	91
94	96	97	98	99	100	101	102	103	104	106	107	108
109	110	111	118	120	121	122	123	124	125	126	129	130
131	132	133	134	135	137	144	145	146	147	148	149	151
152	153	154	155	156	157	158	159	161	164	165	166	167
169	173	180	181	182	183	185	188	189	190	193	194	195
198	199	201	203	210	211	214	215	217	218	219	222	225
227	229	230	231	233	235	237	246	249				

Table 4. All  $\kappa$ = 3 Rules

27	29	39	46	53	58	71	78	83
92	105	114	116	139	141	150	163	172
177	184	197	202	209	216	226	228	

### E. Templates

Three templates are needed to program a CNN universal chip: the A template, the B template, and the z template (Figure 8). The A template is the feedback term of the CNN nonlinear differential equation. For simplicity and robustness,  $a_{00}$  is chosen to be 1, while the other cells of the templates are 0. In the linearly-separable cases, the B and z templates are obtained from the *orientation vector* [Chua et al, 2002] and [Dogaru & Chua, 1998], or normal vector, and the offset of the single separating plane respectively. These templates also convey the equation that describes the outputs of the corresponding truth table. Usually, the output equation is a *signum* function, *sgn*, involving analytical variables  $u_{i-1}$ ,  $u_i$ ,  $u_{i+1}$ , since the CNN chip operates analytically. This signum function can be converted into a *sign* function,

 $\boldsymbol{a}$ , involving symbolic variables  $x_{i-1}$ ,  $x_i$ ,  $x_{i+1}$  in accordance to symbolic truth tables for better understanding. The signum and sign functions are presented in Figure 7. The separating plane and resulting B and z templates are shown in Figure 8 for Rule 204, which is linearly separable.



Figure 7. y = sgn(x) and y = s(x), respectively.



Figure 8. The Standard 1-D CA Templates and the derivation of the templates for Rule 204.

Rules that have higher complexity indices are not linearly-separable, but they always can be decomposed into two or three linearly-separable Rules by Boolean Operations (AND, OR). These Rules are also known as *linearly non-separable* Rules. An example is Rule 184, which is equivalent to Rule 186 AND Rule 248 as presented by Figure 9. Table 5 provides a synthesis of all the higher complexity Rules.



Figure 9. Rule 184 is Rule 186 AND Rule 248.

	_		
Rule N	Synth	esis using	g Rules from Table 1
Rule 6	Rule 7	AND	Rule 14
Rule 9	Rule 11	AND	Rule 13
Rule 18	Rule 19	AND	Rule 50
Rule 20	Rule 21	AND	Rule 84
Rule 22	Rule 23	AND	Rule 254
Rule 24	Rule 31	AND	Rule 248
Rule 25	Rule 59	AND	Rule 221
Rule 26	Rule 31	AND	Rule 250
Rule 27	Rule 31	AND	Rule 251
Rule 28	Rule 31	AND	Rule 220
Rule 29	Rule 31	AND	Rule 93
Rule 30	Rule 31	AND	Rule 254
Rule 33	Rule 35	AND	Rule 49
Rule 36	Rule 47	AND	Rule 244
Rule 37	Rule 47	AND	Rule 117
Rule 38	Rule 55	AND	Rule 238
Rule 39	Rule 47	AND	Rule 55
Rule 40	Rule 42	AND	Rule 168
Rule 41	Rule 43	AND	Rule 253
Rule 44	Rule 47	AND	Rule 236
Rule 45	Rule 47	AND	Rule 253
Rule 46	Rule 47	AND	Rule 254
Rule 52	Rule 55	AND	Rule 244
Rule 53	Rule 55	AND	Rule 245
Rule 54	Rule 55	AND	Rule 254
Rule 56	Rule 59	AND	Rule 248

Rule N Synthesis using Rules from Table 1 Rule 57 Rule 59 AND Rule 253 Rule 58 Rule 59 AND Rule 254 Rule 60 Rule 63 AND Rule 252 Rule 61 AND Rule 63 Rule 253 Rule 62 Rule 63 AND Rule 254 Rule 65 Rule 69 AND Rule 81 Rule 66 Rule 79 AND Rule 242 Rule 67 Rule 79 AND Rule 243 Rule 70 AND Rule 206 Rule 87 Rule 71 Rule 79 AND Rule 87 Rule 72 AND Rule 232 Rule 76 Rule 73 Rule 77 AND Rule 251 Rule 74 Rule 79 AND Rule 234 Rule 75 Rule 79 AND Rule 251 Rule 78 Rule 79 AND Rule 254 Rule 82 Rule 87 AND Rule 250 Rule 83 Rule 87 AND Rule 243 Rule 86 Rule 87 AND Rule 254 Rule 88 Rule 93 AND Rule 248 Rule 89 Rule 93 AND Rule 251 Rule 90 Rule 95 AND Rule 250 Rule 91 Rule 95 AND Rule 251 AND Rule 92 Rule 95 Rule 220 Rule 94 Rule 95 AND Rule 254 Rule 96 Rule 112 AND Rule 224 Rule 113 AND Rule 97 Rule 239

Table 5. Synthesis of Linearly	Non-Separable Boolean	Rules via Boolean Ope	eration (AND, OR) u	using Linearly-Separable Rules
2 2 2		1		

Rule N	Synthe:	sis using	Rules from Table 1
Rule 98	Rule 115	AND	Rule 234
Rule 99	Rule 115	AND	Rule 239
Rule 100	Rule 117	AND	Rule 238
Rule 101	Rule 117	AND	Rule 239
Rule 102	Rule 119	AND	Rule 238
Rule 103	Rule 119	AND	Rule 239
Rule 104	Rule 127	AND	Rule 232
Rule 105	(Rule 43 (	OR Rule	64) AND Rule 253
Rule 106	Rule 127	AND	Rule 234
Rule 107	Rule 43	OR	Rule 64
Rule 108	Rule 127	AND	Rule 236
Rule 109	Rule 32	OR	Rule 77
Rule 110	Rule 127	AND	Rule 238
Rule 111	Rule 127	AND	Rule 239
Rule 114	Rule 115	AND	Rule 242
Rule 116	Rule 117	AND	Rule 252
Rule 118	Rule 119	AND	Rule 254
Rule 120	Rule 127	AND	Rule 248
Rule 121	Rule 8	OR	Rule 113
Rule 122	Rule 127	AND	Rule 250
Rule 123	Rule 127	AND	Rule 251
Rule 124	Rule 127	AND	Rule 252
Rule 125	Rule 127	AND	Rule 253
Rule 126	Rule 127	AND	Rule 254
Rule 129	Rule 143	AND	Rule 241
Rule 130	Rule 138	AND	Rule 162

Table 5 (continued)

Rule N	Synthes	sis using	Rules from Table 1
Rule 131	Rule 143	AND	Rule 243
Rule 132	Rule 140	AND	Rule 196
Rule 133	Rule 143	AND	Rule 245
Rule 134	Rule 142	AND	Rule 247
Rule 135	Rule 143	AND	Rule 247
Rule 137	Rule 171	AND	Rule 221
Rule 139	Rule 143	AND	Rule 251
Rule 141	Rule 143	AND	Rule 205
Rule 144	Rule 176	AND	Rule 213
Rule 145	Rule 179	AND	Rule 213
Rule 146	Rule 178	AND	Rule 223
Rule 147	Rule 179	AND	Rule 223
Rule 148	Rule 191	AND	Rule 212
Rule 149	Rule 191	AND	Rule 213
Rule 150	(Rule 23 (	OR Rule	128) AND Rule 254
Rule 151	Rule 23	OR	Rule 128
Rule 152	Rule 186	AND	Rule 220
Rule 153	Rule 187	AND	Rule 221
Rule 154	Rule 186	AND	Rule 223
Rule 155	Rule 187	AND	Rule 223
Rule 156	Rule 191	AND	Rule 220
Rule 157	Rule 191	AND	Rule 221
Rule 158	Rule 16	OR	Rule 142
Rule 159	Rule 191	AND	Rule 223
Rule 161	Rule 171	AND	Rule 241
Rule 163	Rule 171	AND	Rule 179

Rule N	Synthe	sis using	Rules from Table 1
Rule 164	Rule 174	AND	Rule 244
Rule 165	Rule 175	AND	Rule 245
Rule 166	Rule 174	AND	Rule 247
Rule 167	Rule 175	AND	Rule 247
Rule 169	Rule 171	AND	Rule 253
Rule 172	Rule 174	AND	Rule 253
Rule 173	Rule 175	AND	Rule 253
Rule 177	Rule 179	AND	Rule 241
Rule 180	Rule 191	AND	Rule 244
Rule 181	Rule 191	AND	Rule 245
Rule 182	Rule 4	OR	Rule 178
Rule 183	Rule 191	AND	Rule 247
Rule 184	Rule 186	AND	Rule 248
Rule 185	Rule 187	AND	Rule 253
Rule 188	Rule 191	AND	Rule 252
Rule 189	Rule 191	AND	Rule 253
Rule 190	Rule 191	AND	Rule 254
Rule 193	Rule 205	AND	Rule 241
Rule 194	Rule 206	AND	Rule 242
Rule 195	Rule 207	AND	Rule 243
Rule 197	Rule 205	AND	Rule 213
Rule 198	Rule 206	AND	Rule 247
Rule 199	Rule 207	AND	Rule 247
Rule 201	Rule 205	AND	Rule 251
Rule 202	Rule 206	AND	Rule 251
Rule 203	Rule 207	AND	Rule 251

Table 5	(continued)

Rule N	Synthes	sis using	Rules from Table 1	
Rule 209	Rule 213	AND	Rule 241	
Rule 210	Rule 223	AND	Rule 242	
Rule 211	Rule 223	AND	Rule 243	
Rule 214	Rule 2	OR	Rule 212	
Rule 215	Rule 223	AND	Rule 247	
Rule 216	Rule 220	AND	Rule 250	
Rule 217	Rule 221	AND	Rule 251	
Rule 218	Rule 223	AND	Rule 250	
Rule 219	Rule 223	AND	Rule 251	
Rule 222	Rule 223	AND	Rule 254	
Rule 225	Rule 239	AND	Rule 241	
Rule 226	Rule 239	AND	Rule 242	
Rule 227	Rule 239	AND	Rule 243	
Rule 228	Rule 239	AND	Rule 244	
Rule 229	Rule 239	AND	Rule 245	
Rule 230	Rule 238	AND	Rule 247	
Rule 231	Rule 239	AND	Rule 247	
Rule 233	Rule 1	OR	Rule 232	
Rule 235	Rule 239	AND	Rule 251	
Rule 237	Rule 239	AND	Rule 253	
Rule 246	Rule 247	AND	Rule 254	
Rule 249	Rule 251	AND	Rule 253	

Therefore, instead of finding the templates for all 256 1-D CA Rules, it is sufficient to implement the templates of the 104 linearly-separable Rules to program the CNN universal chip.

Templates used to program Rule 184									
Analytic Truth Table for Rule 184			Fable 4		Template for Rule 186				
	$\mathbf{u}_{i-1}$	ui	$u_{i+1}$	y <sub>i</sub>		A = 0 1 0 B = 1 1 2 z = 1			
	-1	-1	-1	-1	A-				
	-1	-1	1	-1					
	-1	1	-1	-1		Townships for Deals 249			
	-1	1	1	1	Temp	Template for Rule 248			
	1	-1	-1	1					
	1	-1	1	1					
	1	1	-1	-1	A = 0 1 0 B = 2 1 1	A = 0 1 0 B = 2 1 1 Z = 1			
	1	1	1	1					

Figure 10. In order to program the CNN chip for Rule 184, the templates for Rules 186 and 248 are used.

# F. Optimal Templates

Mathematically speaking, there are an infinite number of possible separating planes. Since the B and z templates are based on the normal vector and the offset of the separating plane, respectively, there are also an infinite number of possible templates per Boolean Rule. This is easily seen in the example of Rule 16, shown in Figure 11.



Figure 11. Here are 3 possible separating planes for Rule 16.

To provide a basis for studies concerning CNN universal chips and Boolean Rules, it is best to adhere to a standard set of templates. Among the infinite template possibilities, there is only one set of *optimal CNN templates*. In this paper, the *optimal separating plane* is defined as the plane that is at the maximum projected distance possible from each of the cube's 8

vertices, but which still separates the red vertices from the blue ones. The corresponding optimal CNN templates are derived from the normal vectors and offsets of these optimal separating planes. An algorithm to find this plane is provided in the Appendix. In short, a plane is selected that satisfactorily separates the red vertices from the blue. The projected distance from each vertex to the plane is found, and the minimum distance is maximized by adjusting the plane until an optimal plane is achieved.

#### 2 Gallery of Templates

The optimal CNN templates of the 104 linearly-separable 1-D CA are implemented and presented in table 6. The truth table, Cube, templates, and output formula are presented for each of the 104 Boolean Rules. The truth tables and output formula use symbolic variables  $x_{i-1}$ ,  $x_i$ ,  $x_{i+1}$  for better understanding, but the templates are found based on analytic variables  $u_{i-1}$ ,  $u_i$ ,  $u_{i+1}$  since the CNN universal chip operates on a numerical analytical basis.



Table 6. A Gallery of Templates of all 104 Linearly Separable CA



















































### **3** Concluding Remarks

After compiling a library of optimal CNN templates for linearly-separable 1-D CA, a next step would be to optimize the current library for 2-D CA. Interested readers may browse the Appendix to use the algorithm to implement the optimal CNN templates for linearly-separable 1-D CA, and then move on to investigating 2-D CA. In the process of compiling the optimal CNN templates for linearly-separable 1-D CA, differences between the optimal CNN templates and those provided in [Chua, et al, 2002] may be noted. In particular, the templates for Rule 63 are incorrect, and should be revised as follows:  $[b_1, b_2, b_3]$  should equal to [-1, -1, 0] instead of [0, -1, 0]. To check the validity of the templates generated by the algorithm, the CANDY simulator was run and the dynamic firing patterns were compared.

### 4 Acknowledgements

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## Appendix

In order to find the optimal separating plane, we use the concept of Support Vector Machines [Moore, 2007]. Often we are interested in classifying data. These data points may not necessarily be points in  $\Re^2$  but may be multidimensional  $\Re^n$  points. We are interested in whether we can separate them by a n-1 dimensional hyperplane. This is a typical form of linear classifier. There are many linear classifiers that might satisfy this property. However, we are additionally interested to find out if we can achieve maximum separation (margin) between the two classes. Now, if such a hyperplane exists, the hyperplane is clearly of interest and is known as the maximum-margin hyperplane.



Figure 12. Maximum-margin hyperplanes for a SVM trained with samples from two classes. Samples along the hyperplanes are called support vectors

Consider Figure 12. The goal is to separate the "x"s from the "o"s<sup>3</sup> using a hyperplane that is at maximum distance between the two classes. We can consider the data points to be of the form:

$$\{(x_1,c_1),(x_2,c_2),\ldots,(x_n,c_n)\}$$

<sup>&</sup>lt;sup>3</sup> In our case, the "x"s could be the red vertices and the "o"s could be the blue vertices. We have thus colored the "x"s and "o"s that would give rise to the support vectors.

Here the  $c_i$  is either 1 or -1. This constant denotes the class to which point  $x_i$  belongs to (for instance, if the point is an "x" then  $c_i$  is 1 and if the point is a "o" then  $c_i$  is -1). Each  $x_i$  is a n-dimensional real vector, usually of scaled [0,1] or [-1,1] values. Now, the dividing hyperplane takes the form:

$$w \cdot x - b = 0$$

The vector w points perpendicular to the separating hyperplane. Adding the offset parameter b allows us to increase the margin. In its absence, the hyperplane is forced to pass through the origin, restricting the solution. As we are interested in the maximum margin, we are interested in the support vectors and the parallel hyperplanes closest to these support vectors in either class, refer to Figure 12 It can be shown that these hyperplanes can be described by equations:

$$w \cdot x - b = 1,$$
$$w \cdot x - b = -1$$

In our case, the points are linearly separable. Therefore we can select the hyperplanes so that there are no points between them and then try to maximize their distance. By using geometry, we find the distance between the hyperplanes is  $\frac{2}{|w|}$ , so we want to minimize |w|. To exclude data points, we need to ensure that for all *i* either:

$$w \cdot x_i - b \ge 1$$
, or  
 $w \cdot x_i - b \le -1$ 

This can be rewritten as:

$$c_i(w \cdot x_i - b) \ge 1, \quad 1 \le i \le n \tag{1}$$

The problem now is to minimize |w| subject to the constraint in (1). That is:

**Minimize** 
$$|w|$$
 subject to  $c_i(w \cdot x_i - b) \ge 1$ ,  $1 \le i \le n$ 

The equation above can be solved using a mathematical package. We use the MATLAB toolbox from [Schwaighofer, 2002] (you need to have the Optimzation toolbox from Mathworks). First download and unzip the toolbox from [Schwaighofer, 2002]. Here are MATLAB commands to find the normal vector and the offset of the optimal-separating plane for Rule 95. The first line sets up the input vector, the second line the output vector corresponding to rule 95. The last two lines use the SVM toolbox to obtain the normal vector w and the offset b for the optimal separating plane.

```
>> U = [-1 -1 -1;-1 -1 1;-1 1 -1; ...
-1 1 1;1 -1 -1;1 -1 1;1 1 -1;1 1 1];
>> Y95 = [1;1;1;1;1;-1;1;-1];
>> net_setup = svm(3,'linear',[],10);
>> net95 = svmtrain(net_setup,U,Y95)
```