Introduction to Learning Classifier Systems

(mostly XCS)

Stewart W. Wilson
Prediction Dynamics

On the original classifier system...

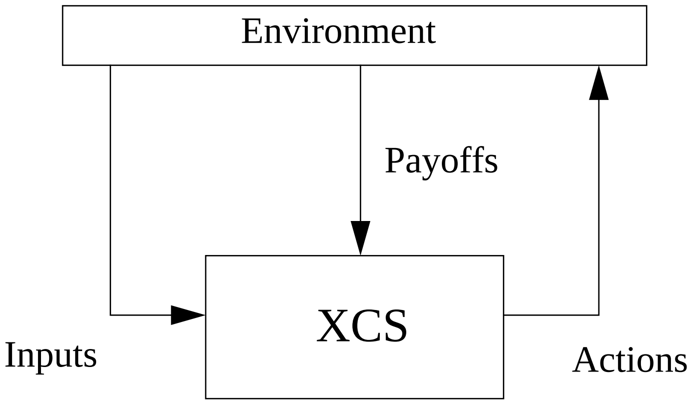
- Holland, J. H. (1986). In *Machine Learning, An Artificial Intelligence Approach. Volume II.*
- Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning.*
- Lashon Booker
- Larry Bull
- Stephanie Forrest
- John Holmes
- Tim Kovacs
- Rick Riolo
- Robert Smith
- Stewart Wilson
- Many others

What is it?

- Learning machine (program).
- Minimum *a priori*.
- “On-line”.
- Capture regularities in environment.

What does it learn?

To get reinforcements (“rewards”, “payoffs”)



(Not “supervised” learning—no prescriptive teacher.)

What inputs and outputs?

Inputs:

Now binary, e.g., 100101110

—like thresholded sensor values.

Later continuous, e.g., <43.0 92.1 7.4 ... 0.32>

Outputs:

Now discrete decisions or actions,

e.g., 1 or 0 (“yes” or “no”),

“forward”, “back”, “left”, “right”

Later continuous, e.g., “head 34 degrees left”

What's going on inside?

XCS contains rules (called *classifiers*), some of which will match the current input. An action is chosen based on the predicted payoffs of the matching rules.

<condition>:<action> => <prediction>.

Example: 01#1## : 1 => 943.2

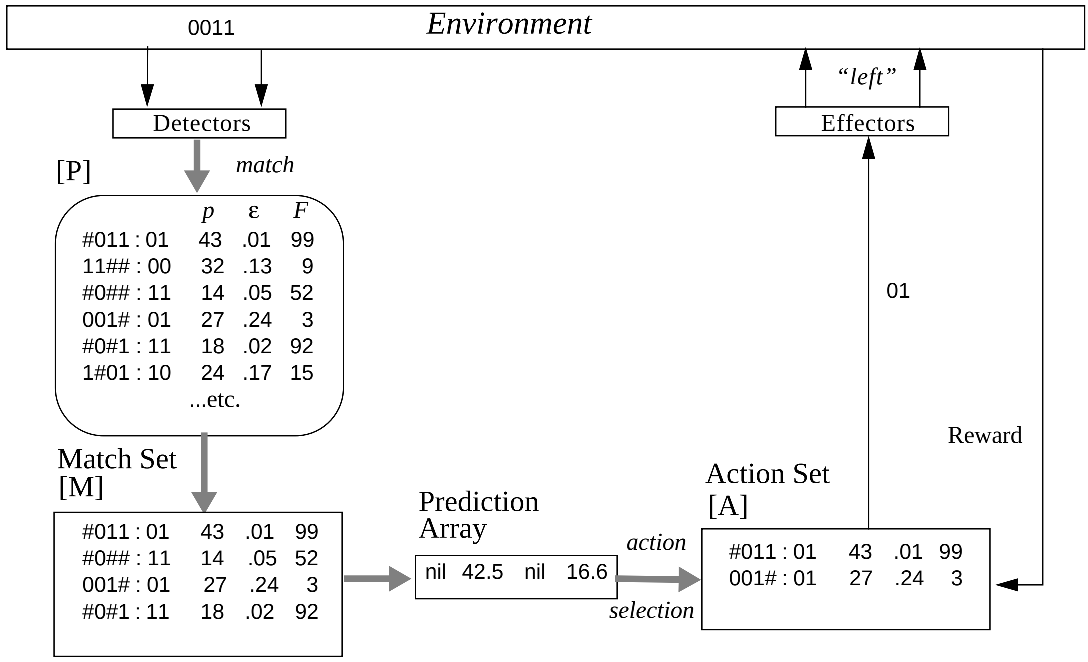
Note this rule matches more than one input string:

010100
010110
010101
011111
011100
011101
011110
011111.

This adaptive "rule-based" system contrasts with "PDP" systems such as NNs in which knowledge is distributed.

XCS

How does the performance cycle work?



- For each action in [M], classifier predictions *p* are weighted by fitnesses *F* to get system's net prediction in the prediction array.
- Based on the system predictions, an action is chosen and sent to the environment.
- Some reward value is returned.

XCS

How do rules acquire their predictions?

1. By "updating" the current estimate.

   For each classifier C_j in the current [A],

   $$p_j \leftarrow p_j + \alpha(R - p_j),$$

   where R is the current reward and α is the learning rate.

   This results in p_j being a "recency weighted" average of previous reward values:

   $$p_j(t) = \alpha R(t) + \alpha(1-\alpha)R(t-1) + \alpha(1-\alpha)^2 R(t-2) + \dots + (1-\alpha)^t p_j(0).$$

2. And by trying different actions, according to an *explore/exploit* regime.

   A typical regime chooses a random action with probability 0.5.

   Exploration (e.g., random choice) is necessary in order to learn anything. But exploitation—picking the highest-prediction action is necessary in order to make best use of what is learned.

   There are many possible explore/exploit regimes, including gradual changeover from mostly explore to mostly exploit.

Where do the rules come from?

- Usually, the “population” [P] is initially empty. (It can also have random rules, or be seeded.)
- The first few rules come from “covering”: if no existing rule matches the input, a rule is created to match, something like imprinting.

  Input: 11000101

  Created rule: 1##0010# : 3 => 10
  Random #’s and action, low initial prediction.

- But primarily, new rules are derived from existing rules.

How are new rules derived?

- Besides its prediction p_j, each classifier's *error* and *fitness* are regularly updated.

Error: $\varepsilon_j \leftarrow \varepsilon_j + \alpha(|R - p_j| - \varepsilon_j)$.

Accuracy: $\kappa_j \equiv \varepsilon_j^{-n}$ if $\varepsilon_j > \varepsilon_0$, otherwise ε_0^{-n}

Relative accuracy: $\kappa_j' \equiv \kappa_j / \left(\sum_i \kappa_i\right)$, over [A].

Fitness: $F_j \leftarrow F_j + \alpha(\kappa_j' - F_j)$.

- Periodically, a *genetic algorithm* (GA) takes place in [A].

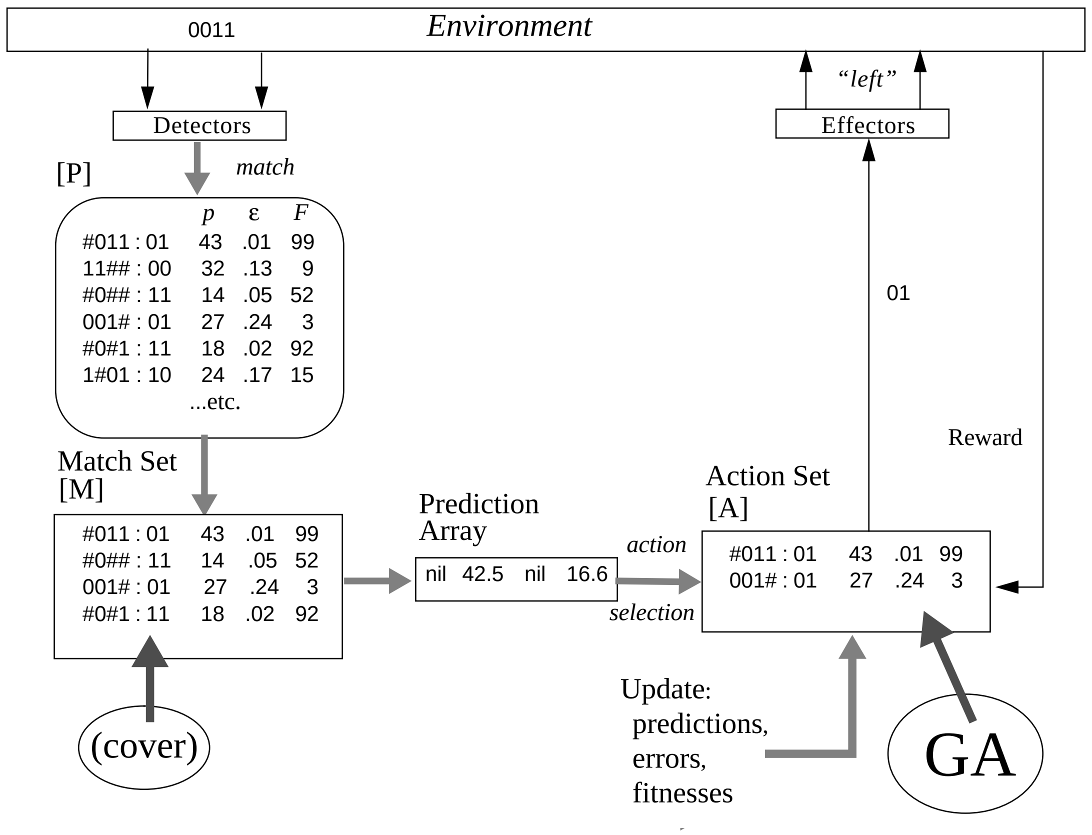
Two classifiers C_i and C_j are selected with probability proportional to fitness. They are copied to form C_i' and C_j'.

With probability χ, C_i' and C_j' are *crossed* to form C_i'' and C_j'', e.g.,

$$\begin{array}{l|l} 1\ 0\ \#\ \# & 1\ 1 : 1 \\ \#\ 0\ 0\ 0 & 1\ \# : 1 \end{array} \quad \Rightarrow \quad \begin{array}{l} 1\ 0\ \#\ \#\ 1\ \# : 1 \\ \#\ 0\ 0\ 0\ 1\ 1 : 1 \end{array}$$

C_i'' and C_j'' (or C_i' and C_j' if no crossover occurred), possibly mutated, are added to [P].

Can I see the overall process?



What happens to the “parents”?

They remain in [P], in competition with their offspring.

But two classifiers are *deleted* from [P] in order to maintain a constant population size.

Deletion is probabilistic, with probability proportional to, e.g.:

- A classifier’s average action set size a_j—estimated and updated like the other classifier statistics.
- a_j/F_j, if the classifier has been updated enough times, otherwise a_j/F_{ave}, where F_{ave} is the mean fitness in [P].

—And other arrangements, all with the aim of balancing resources (classifiers) devoted to each niche ([A]), but also eliminating low fitness classifiers rapidly.

What are the results like? — 1

Basic example for illustration: Boolean 6-multiplexer.

$$1\ 0\ 1\ 0\ 0\ 1 \rightarrow \boxed{F_6} \rightarrow 0$$

1 0 1 0 0 1

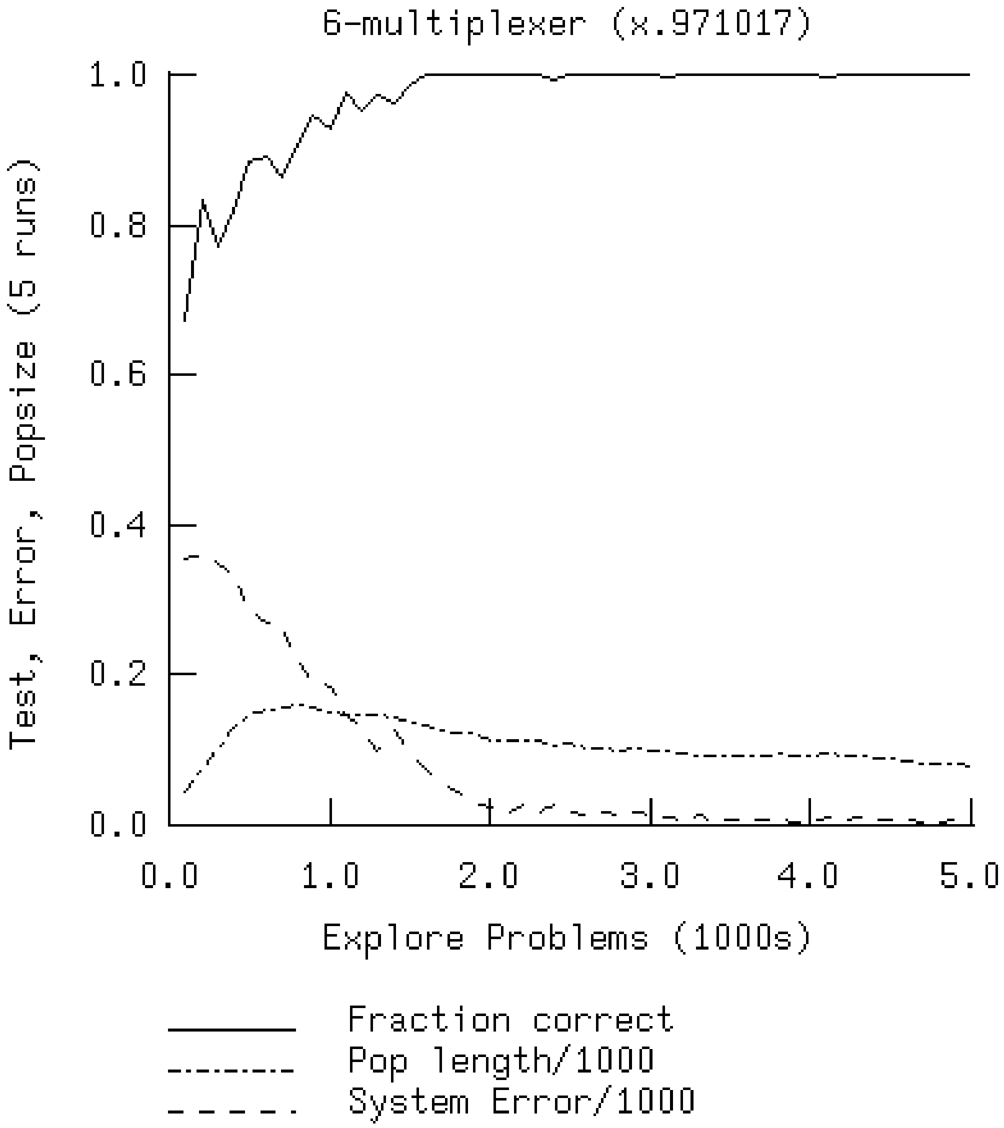
$$F_6 = x_0'x_1'x_2 + x_0'x_1x_3 + x_0x_1'x_4 + x_0x_1x_5$$

$\boldsymbol{l = k + 2^k} \quad \boldsymbol{k} > 0$

$$\begin{aligned} F_{20} = {} & x_0'x_1'x_2'x_3'x_4 + x_0'x_1'x_2'x_3x_5 + \\ & x_0'x_1'x_2x_3'x_6 + x_0'x_1'x_2x_3x_7 + \\ & x_0'x_1x_2'x_3'x_8 + x_0'x_1x_2'x_3x_9 + \\ & x_0'x_1x_2x_3'x_{10} + x_0'x_1x_2x_3x_{11} + \\ & x_0x_1'x_2'x_3'x_{12} + x_0x_1'x_2'x_3x_{13} + \\ & x_0x_1'x_2x_3'x_{14} + x_0x_1'x_2x_3x_{15} + \\ & x_0x_1x_2'x_3'x_{16} + x_0x_1x_2'x_3x_{17} + \\ & x_0x_1x_2x_3'x_{18} + x_0x_1x_2x_3x_{19} \end{aligned}$$

$$01100010100100001000 \rightarrow 0$$

What are the results like?— 2



What are the results like?— 3

Population at 5,000 problems in descending order of numerosity (first 40 of 77 shown).

				PRED	ERR	FITN	NUM	GEN	ASIZ	EXPER	TST
0.	11	##	#0	1	0.	.00	884.	30	.50	31.2	287	4999
1.	00	1#	##	0	0.	.00	819.	24	.50	25.9	286	4991
2.	01	#1	##	1	1000.	.00	856.	22	.50	24.1	348	4984
3.	01	#1	##	0	0.	.00	840.	20	.50	21.8	263	4988
4.	11	##	#1	0	0.	.00	719.	20	.50	22.6	238	4972
5.	00	1#	##	1	1000.	.00	698.	19	.50	20.9	222	4985
6.	01	#0	##	0	1000.	.00	664.	18	.50	23.9	254	4997
7.	10	##	1#	1	1000.	.00	712.	18	.50	22.4	236	4980
8.	00	0#	##	0	1000.	.00	674.	17	.50	21.2	155	4992
9.	10	##	0#	0	1000.	.00	706.	17	.50	19.9	227	4990
10.	11	##	#0	0	1000.	.00	539.	17	.50	24.5	243	4978
11.	10	##	1#	0	0.	.00	638.	16	.50	20.0	240	4994
12.	01	#0	##	1	0.	.00	522.	15	.50	23.5	283	4967
13.	00	0#	##	1	0.	.00	545.	14	.50	20.9	110	4979
14.	10	##	0#	1	0.	.00	425.	12	.50	23.0	141	4968
15.	11	##	#1	1	1000.	.00	458.	11	.50	21.1	76	4983
16.	11	##	11	1	1000.	.00	233.	6	.33	22.1	130	4942
17.	0#	00	##	1	0.	.00	210.	6	.50	23.1	221	4979
18.	11	##	01	1	1000.	.00	187.	5	.33	21.1	86	4983
19.	01	10	##	1	0.	.00	168.	4	.33	19.1	123	4939
20.	11	#1	#0	0	1000.	.00	114.	4	.33	26.2	113	4978
21.	10	##	11	0	0.	.00	152.	4	.33	23.9	34	4946
22.	10	1#	0#	1	0.	.00	131.	3	.33	21.7	111	4968
23.	00	0#	0#	0	1000.	.00	117.	3	.33	22.8	57	4992
24.	11	1#	#0	0	1000.	.00	68.	3	.33	28.7	38	4978
25.	10	#1	0#	0	1000.	.00	46.	3	.33	20.6	4	4990
26.	10	##	11	1	1000.	.00	81.	3	.33	23.9	113	4950
27.	#1	#0	#0	0	1000.	.00	86.	3	.50	23.6	228	4981
28.	01	10	##	0	1000.	.00	61.	2	.33	22.5	16	4997
29.	01	00	##	0	1000.	.00	58.	2	.33	22.2	46	4981
30.	10	0#	0#	1	0.	.00	63.	2	.33	22.8	22	4866
31.	11	0#	#1	1	1000.	.00	63.	2	.33	23.2	35	4953
32.	00	1#	#0	1	1000.	.00	77.	2	.33	20.7	7	4985
33.	10	#1	0#	1	0.	.00	93.	2	.33	24.5	28	4968
34.	11	#1	#1	1	1000.	.00	59.	2	.33	21.8	12	4983
35.	01	#1	#0	1	1000.	.00	75.	2	.33	23.1	21	4944
36.	01	#0	#1	0	1000.	.00	36.	2	.33	21.7	3	4997
37.	11	##	01	0	0.	.00	92.	2	.33	19.7	41	4948
38.	10	##	##	1	703.	.31	8.	2	.67	22.3	10	4980
39.	#1	1#	#0	0	856.	.22	11.	2	.50	27.4	22	4978

XCS

Can you show the evolution of a rule?

Action sets [A] for input 101001 and action 0 at several epochs.

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			PRED	ERR	FITN	NUM	GEN	ASIZ	EXPER	TST
0.	## ## ##	0	431.	.440	8.	2	1.00	17.2	76	244
1.	## 10 ##	0	245.	.362	109.	2	.67	10.6	14	236
2.	## 10 0#	0	893.	.146	504.	5	.50	11.2	8	200

1135

			PRED	ERR	FITN	NUM	GEN	ASIZ	EXPER	TST
0.	## #0 #1	0	519.	.419	1.	1	.67	16.5	11	1134
1.	## #0 0#	0	510.	.390	27.	2	.67	16.8	15	1119
2.	## 1# ##	0	125.	.261	0.	1	.83	21.7	18	1132
3.	#0 ## 0#	0	1000.	.021	4.	1	.67	17.7	0	1117
4.	#0 10 ##	0	454.	.433	2.	1	.50	14.8	53	1106
5.	#0 10 0#	0	735.	.343	27.	2	.33	14.4	13	1106
6.	1# ## #1	0	169.	.282	2.	1	.67	24.4	12	1119
7.	1# ## 0#	0	445.	.418	13.	5	.67	18.6	27	1119
8.	10 ## ##	0	1000.	.000	135.	2	.67	24.2	3	1117
9.	10 ## 0#	0	1000.	.000	451.	3	.50	23.4	17	1117

1333

			PRED	ERR	FITN	NUM	GEN	ASIZ	EXPER	TST
0.	#0 1# 0#	0	761.	.336	1.	1	.50	10.6	10	1325
1.	1# ## 0#	0	652.	.387	5.	1	.67	10.9	11	1325
2.	1# #0 #1	0	107.	.197	6.	1	.50	22.0	8	1308
3.	1# 10 0#	0	829.	.228	26.	2	.33	14.3	9	1325
4.	10 ## 0#	0	1000.	.000	490.	4	.50	11.6	26	1325

2410

			PRED	ERR	FITN	NUM	GEN	ASIZ	EXPER	TST
0.	1# ## 0#	0	360.	.394	0.	1	.67	18.1	14	2404
1.	10 ## 0#	0	1000.	.000	478.	10	.50	20.1	95	2392

2725

			PRED	ERR	FITN	NUM	GEN	ASIZ	EXPER	TST
0.	#0 ## 0#	0	863.	.237	0.	3	.67	21.1	18	2714
1.	10 ## 0#	0	1000.	.000	630.	13	.50	22.6	117	2714
2.	10 #0 0#	0	1000.	.000	49.	1	.33	22.4	9	2638
3.	10 1# 0#	0	1000.	.000	58.	1	.33	18.4	8	2693

Why accurate, *maximally general* rules?

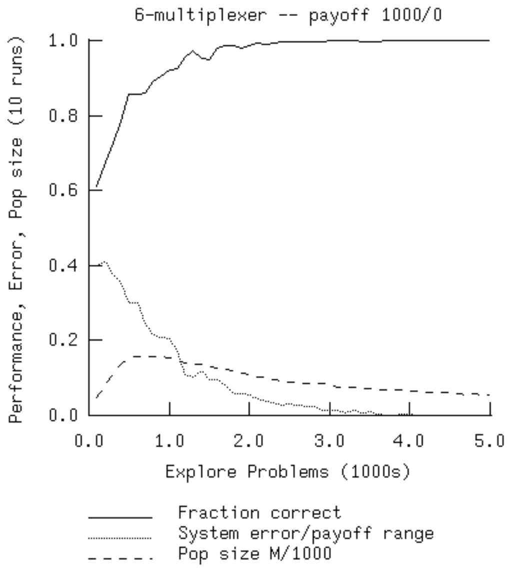
Consider two classifiers C1 and C2 having the same action, and let C2 be a generalization of C1. That is, C2 can be obtained from C1 by changing some non-# alleles in the condition to #'s. Suppose that C1 and C2 are equally accurate. They will therefore have the same fitness. However, note that, since it is more general, C2 will occur in *more action sets* than C1. What does this mean? Since the GA acts in the action sets, C2 will have *more reproductive opportunities* than C1. This edge in reproductive opportunities will cause C2 to gradually drive C1 out of the population.

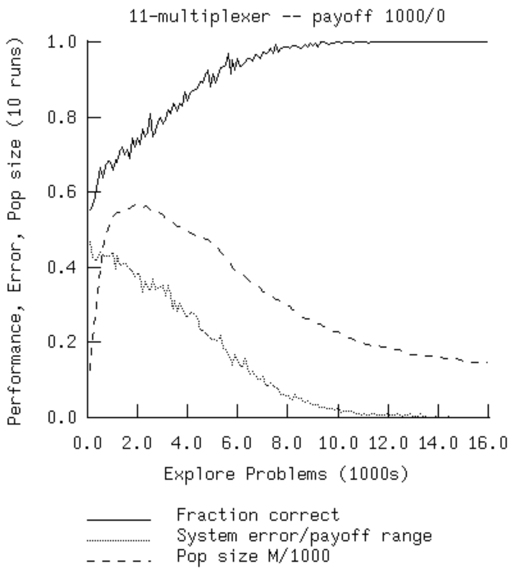
Example:			p	ε	F
C1:	1 0 # 0 0 1 : 0	$\Rightarrow$	1000	.001	920
C2:	1 0 # # 0 # : 0	$\Rightarrow$	1000	.001	920

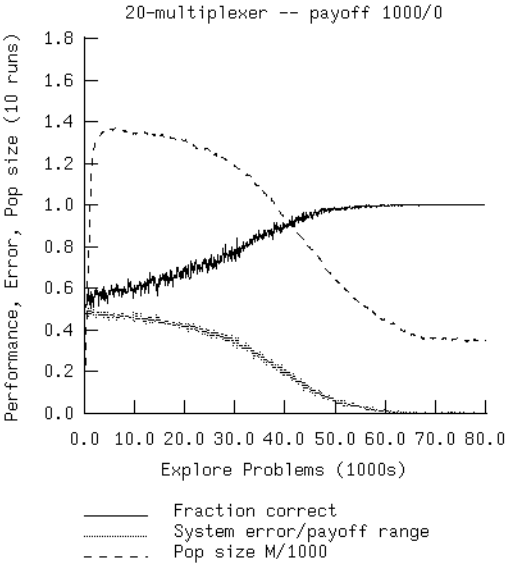
C2 has equal fitness but more reproductive opportunities than C1.

C2 will "drive out" C1

Does XCS scale up?







What about complexity?

20m ~5x harder than 11m
11m ~5x harder than 6m.

$$\Rightarrow \; D = cg^p,$$

where D = “difficulty”, here learning time,
g = number of maximal generalizations,
p = a power, about 2.3
c = a constant about 3.2

Thus “D is polynomial in g”.

What is D with respect to l, string length?

For the multiplexers, $l = k + 2^k$,
or $l \rightarrow 2^k$ for large k.

But $g = 4 \cdot 2^k$, thus $l \sim g$,
So that “D is polynomial in l” (not exponential).

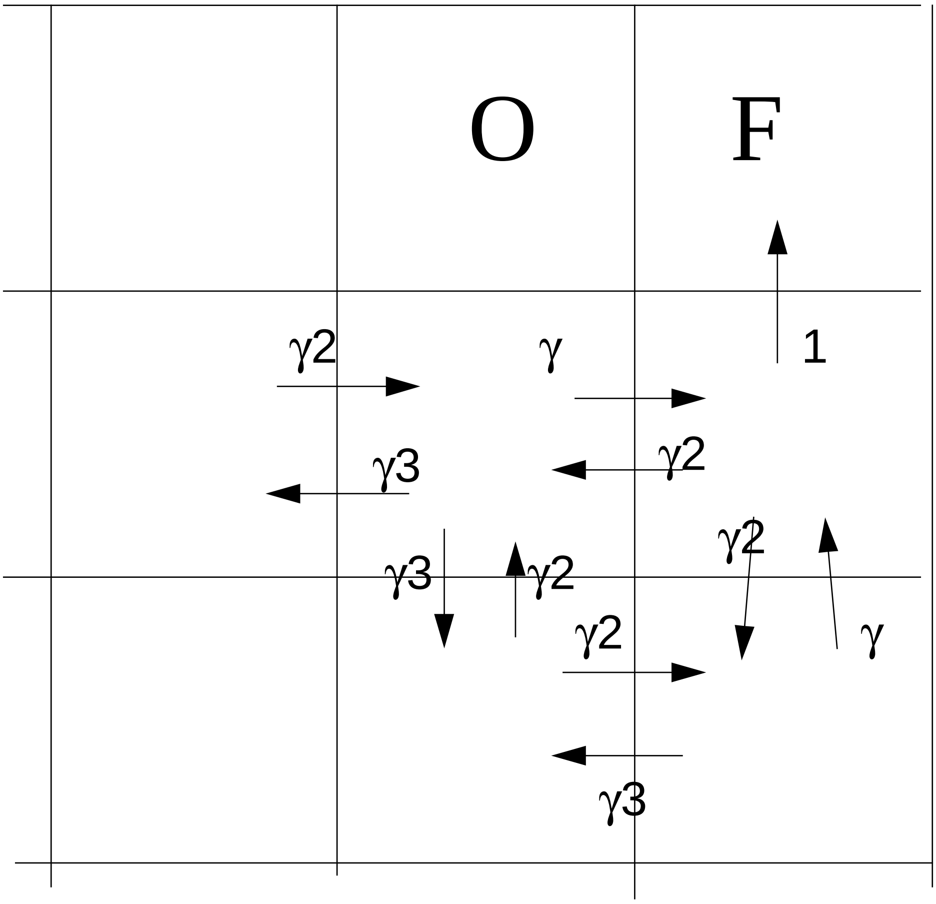
What about deferred reward?

Apply ideas from multi-step reinforcement learning.

Need the *action-value* of each action in each state.

What is the action-value of a state more than one step from reward?

Intuitive sketch:

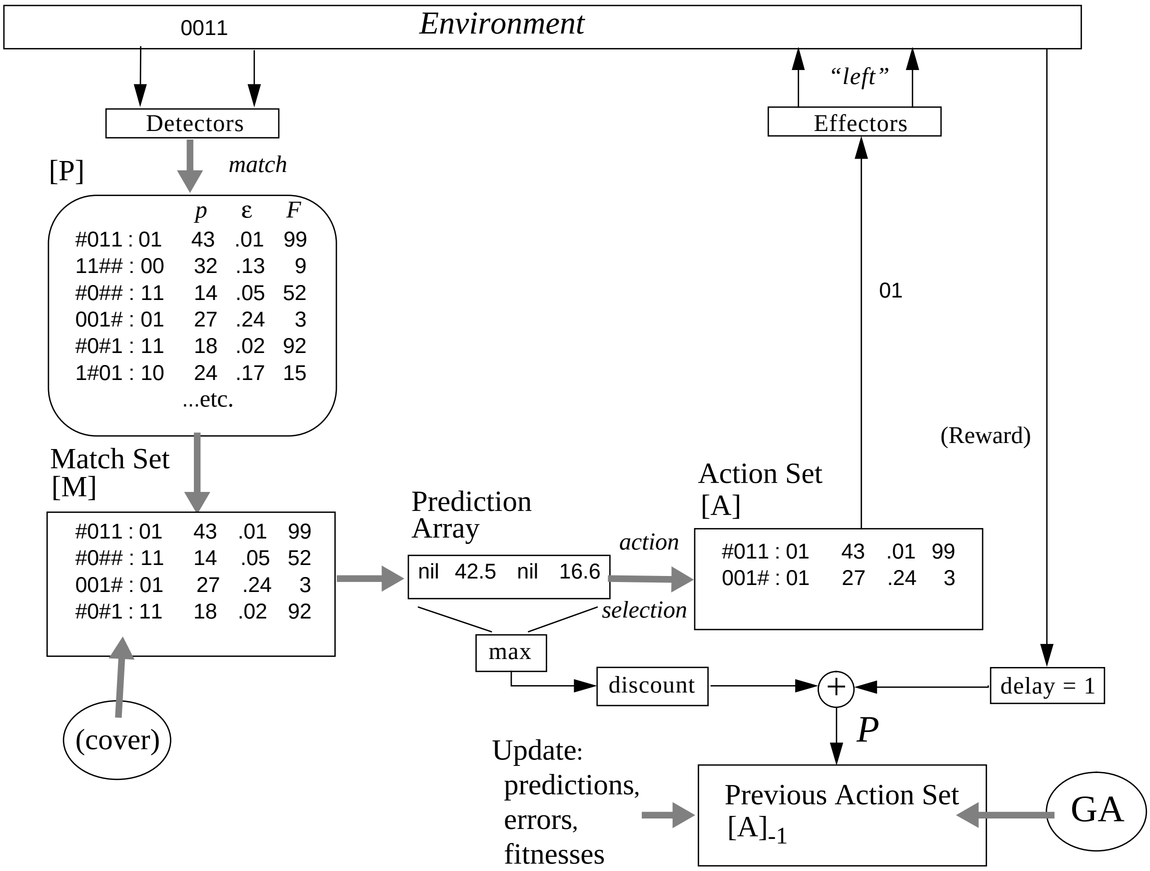


$$p_j \leftarrow p_j + \alpha[(r_{\mathrm{imm}} + \gamma \max_{a' \in A} P(x',a')) - p_j]$$

where p_j is the prediction of a classifier in the current action set [A],
x' and a' are the next state and possible actions,
$P(x',a')$ is a system prediction at the next state,
and r_{imm} is the current external reward.

XCS

Can I see the overall process?



- Previous action set $[A]_{-1}$ is saved and updates are done there, using the current prediction array for "next state" system predictions.
- On the last step of a problem, updates occur in [A].

XCS

What are the results like?— 1

```
..............................
.QQF..QQF..OQF..QQG..OQG..OQF.
.OOO..QOO..OQO..OOQ..QQO..QQQ.
.OOQ..OQQ..OQQ..QQO..OOO..QQO.
..............................
..............................
.QOF..QOG..QOF..OOF..OOG..QOG.
.QQO..QOO..OOO..OQO*.QQO..QOO.
.QQQ..OOO..OQO..QOQ..QOQ..OQO.
..............................
..............................
.QOG..QOF..OOG..OQF..OOG..OOF.
.OOQ..OQQ..QQO..OQQ..QQO..OQQ.
.QQO..OOO..OQO..OOQ..OQQ..QQQ.
..............................
```

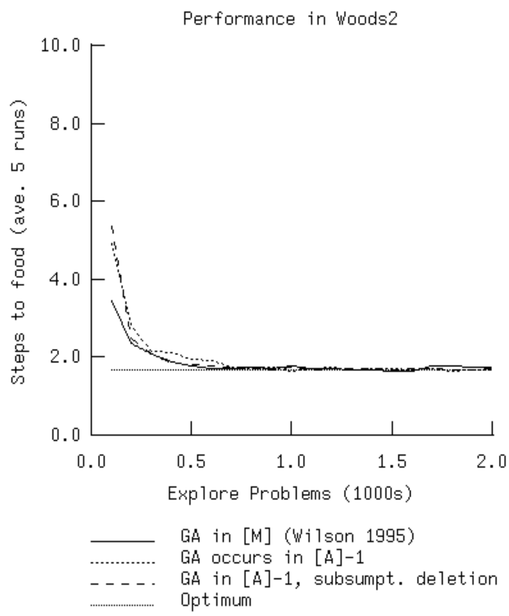
- Animat senses the 8 adjacent cells.

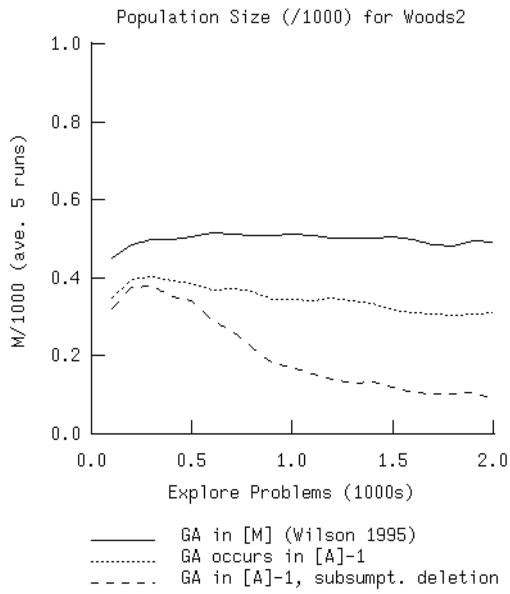
F b b
O * b
Q b b

- Coding of each object:

F = 110 “food1”
G = 111 “food2”
O = 010 “rock1”
Q = 011 “rock2”
b = 000 “blank”

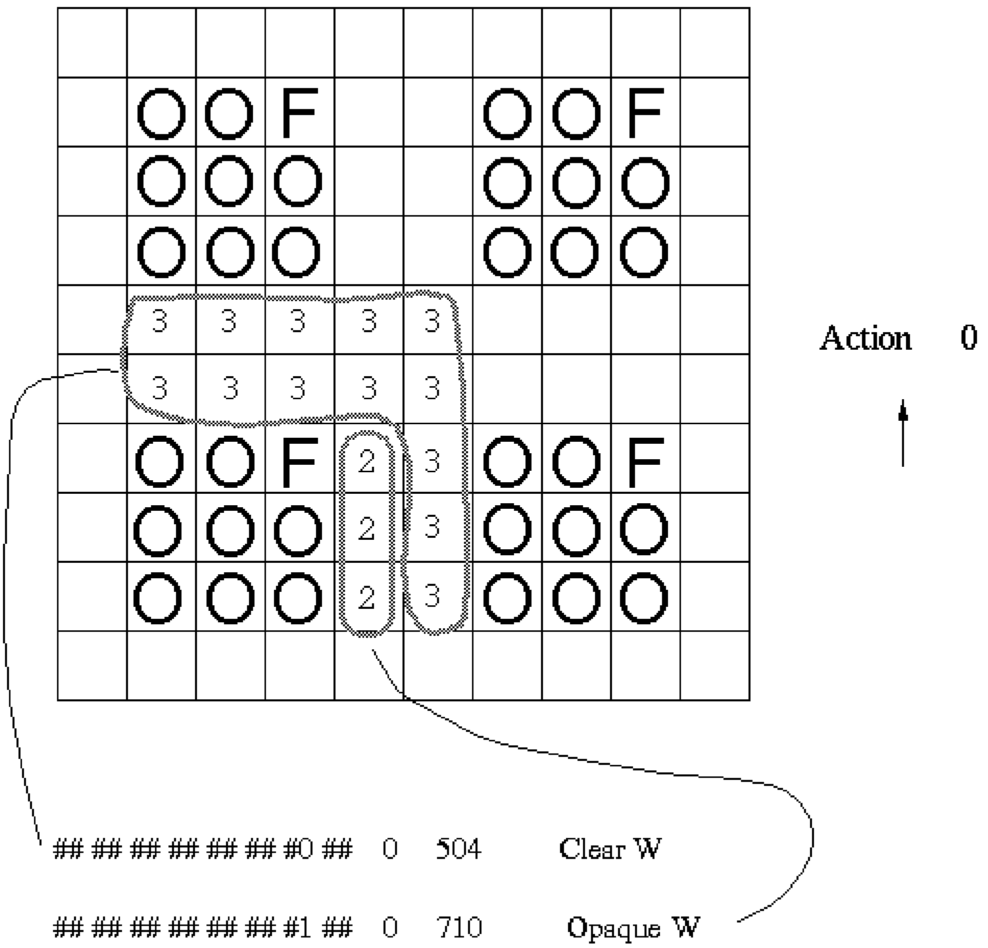
- “Sense vector” for above situation: 000000000000000011010110
- A matching classifier: ####0#00####00001##101## : 7





What are the results like?— 2

Two generalizations discovered by XCS in Woods1.



(Food = 11 = “Tasty”, “Opaque”
Rock = 01 = “Bland”, “Opaque”
Blank = 00 = “Bland”, “Clear”)

What about non-binary inputs?

Each input variable x_i may be real or integer valued.

Classifier: $< (x_{1l}, x_{1u})$ ... $(x_{nl}, x_{nu}) >$: $< action > \Rightarrow p$

- Condition consists of "interval predicates"
  $int_i = (x_{il}, x_{iu})$.

- Classifier matches iff $x_{il} \leq x_i < x_{iu}, \ \forall i$.

- Crossover occurs between and within predicates.

- Mutation adds $\pm rand(m_1)$ to allele.
  [m_1 is real or integer as appropriate.]

- Covering creates a classifier with condition in which
  $x_{il} = max[(x_i - rand(m_2)), x_{iMIN}]$
  $x_{iu} = min[(x_i + rand(m_2)), x_{iMAX}]$

Example: Wisconsin Breast Cancer dataset

- Sample instances (699 in all).

  1070935,3,1,1,1,1,1,2,1,1,2
  1071760,2,1,1,1,2,1,3,1,1,2
  1072179,10,7,7,3,8,5,7,4,3,4
  1074610,2,1,1,2,2,1,3,1,1,2
  1075123,3,1,2,1,2,1,2,1,1,2
  1079304,2,1,1,1,2,1,2,1,1,2
  1080185,10,10,10,8,6,1,8,9,1,4
  1081791,6,2,1,1,1,1,7,1,1,2
  1084584,5,4,4,9,2,10,5,6,1,4
  1091262,2,5,3,3,6,7,7,5,1,4
  1096800,6,6,6,9,6,?,7,8,1,2

- *Clump Thickness, Uniformity of Cell Size, Uniformity of Cell Shape, Marginal Adhesion, Single Epithelial Cell Size, Bare Nuclei, Bland Chromatin, Normal Nucleoli, Mitoses.*

- 458 Benign + 241 Malignant = 699 Cases.

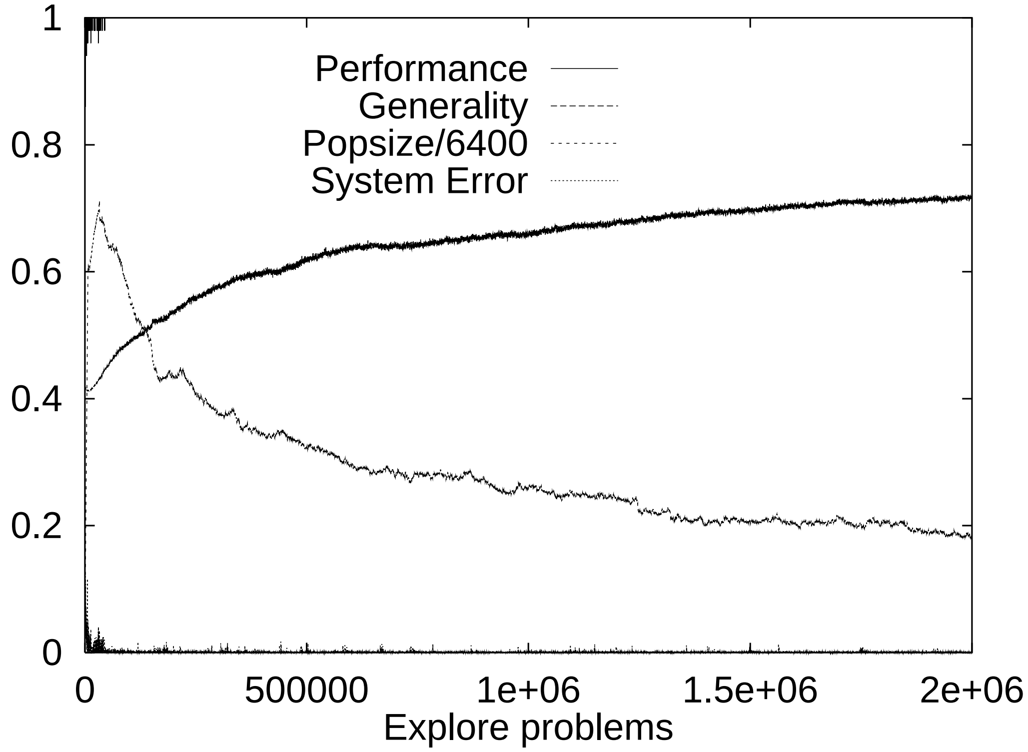
- Stratified 10-fold cross-validation result:

Correct	Incorrect	Not Matched	Fraction Correct
68	2	0	0.9714
69	1	0	0.9857
65	5	0	0.9286
66	4	0	0.9429
65	3	2	0.9286
64	3	3	0.9143
70	0	0	1.0000
69	1	0	0.9857
65	3	1	0.9420
67	2	1	0.9571
		MEAN $\Rightarrow$	0.9556

- Performance similar to best other systems.

What about generalization?

Increasingly general, accurate classifiers were found by continuing the evolution.



If clump thickness is 7 or above and uniformity of cell size is 5 or above, malignancy is indicated.

If normal nucleoli is 10, then malignant.

If uniformity of cell shape is 8 or above and marginal adhesion is not 1, then malignant.

If uniformity of cell size is 1 and bare nuclei is 4 or less, then benign.

What if generalizations are not conjunctive?

"Standard" classifier condition is a conjunction of variable values or ranges:

#10#1# or (3,7)(0,2) ... (4,9) etc.

What about "if $x > y$ for any x and y, and action a is taken, payoff is predicted to be p" ?

Cannot be represented by a single conjunctive condition, since it's a relation.

However, it can be represented using an **S-classifier**:

$$(x > y) : a \Rightarrow p$$

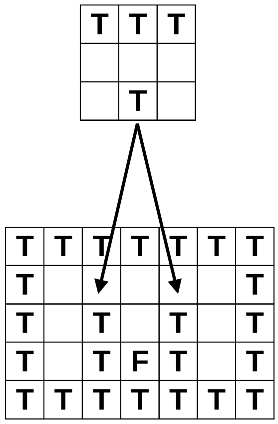
I.e., a classifier whose condition is a Lisp S-expression.

With appropriate elementary functions, S-classifiers can encode an almost unlimited variety of conditions.

They can be evolved using techniques drawn from genetic programming.

What about Non-Markov environments?

Example (McCallum's Maze):



Arrows indicate aliased states—each has the same local view. The optimal action is not determinable from the sensory input.

Approaches:

- "History window"—remember previous inputs
- Search for correlation with past input events
- **Adaptive internal state**

Adaptive internal state?

$$< Environmental\ condition >< Internal\ condition > : \\ < Internal\ action >< External\ action > \Rightarrow p$$

Example: ###1##0# # : 1 0 ⇒ 504

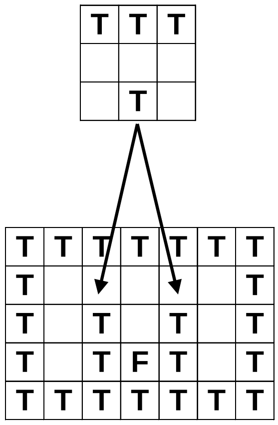
Internal action modifies an internal register **R**.
Internal condition reads (must match) **R**.
Internal state = current contents of **R**.

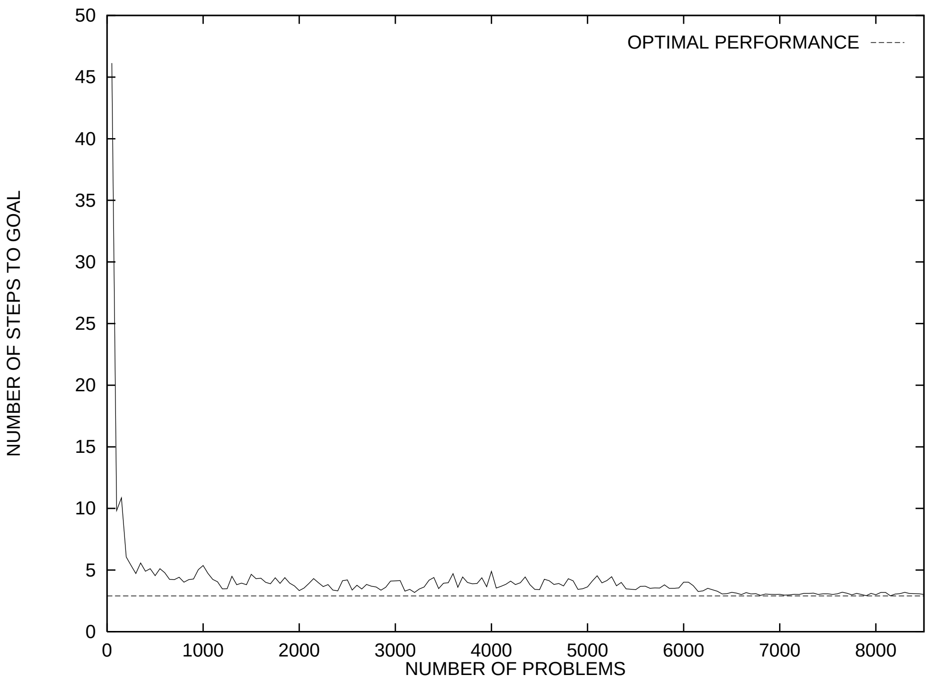
For a 1-bit register:

If internal action = 1, set **R** to 1
= 0, set **R** to 0
= #, leave **R** unchanged

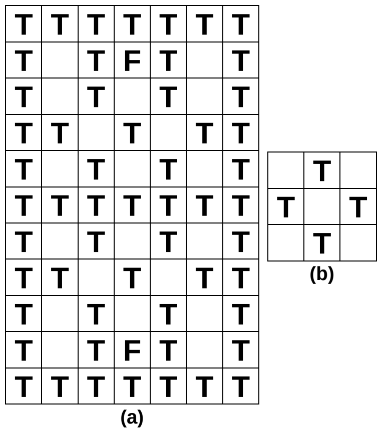
Will classifiers evolve that set and read **R** so as to distinguish aliased states and achieve high performance?

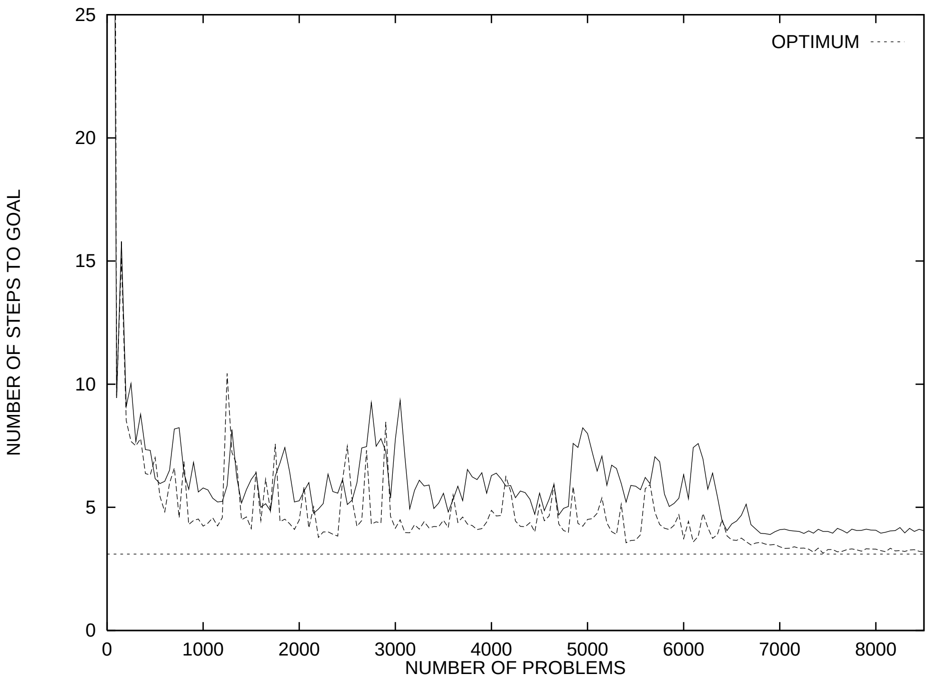
Woods101 (= McCallum's Maze)





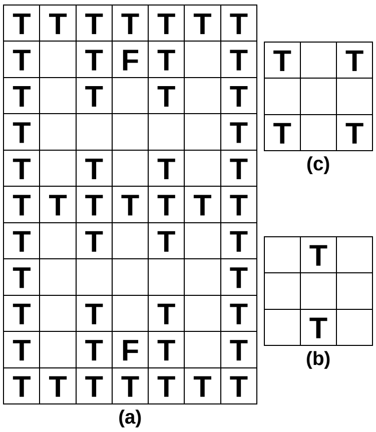
Woods101.5

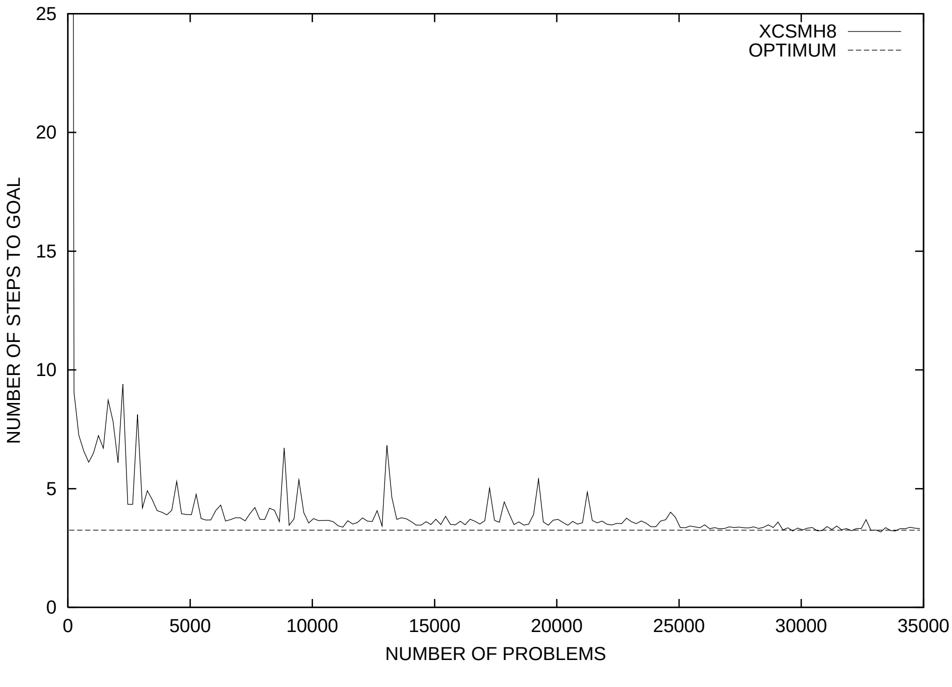




Optimum reached with register redundancy
(4 bits vs. 2).

Woods102





Uses 8-bit register.

Directions — 1

- **Generalized classifier** (GCL) architecture:

  $$t(x) \;:\; r(a) \;\Rightarrow p(x,a)$$

  "For x in the subdomain given by $t(x)$ and a satisfying the *action restriction* $r(a)$, the prediction is given by $p(x,a)$"

  GCL opens way to **continuous** (non-discrete) actions and maybe to continuous time.

- **Anticipatory** classifier systems that predict the next state. Individual classifiers predict entire state, or individual classifiers predict state components.

- Continue Non-Markov work to create **Hierarchical** LCS with sub-behaviors selected and controlled by higher behaviors. Based on extensions of the register idea.

Directions — 2

- Theory of XCS **learning complexity**. Time to performance, memory required. Hypothesis is that complexity is a low-order polynomial in target function complexity—in contrast to other learning methods.

- Improvements to XCS **mechanisms**. More sophisticated accuracy measures. Tournament selection. Long-path techniques.

- Comparison of XCS and **strength-based** (traditional) classifier systems. Does the traditional system have a niche? Where is accuracy-based weak?

How is XCS different from other RL systems?

- Rule-based, not connectionist or rbf-like
- Structure is created as needed
- Learning may often be faster because classifiers are inherently non-linear
- Learning complexity tractable
- Classifiers can keep and use statistics; difficult in a network
- User can "see the knowledge"
- Hierarchy and reasoning may be easier, since knowledge is in the form of discrete rules
- Powerful generalization ability, if syntax suits the problem domain