

## On the traditional 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
- Stephanie Forrest
- John Holmes
- Tim Kovacs
- Rick Riolo
- Robert Smith
- Tom Westerdale
- (Stewart Wilson)
- Many others

What about real inputs?

- Temperature, concentration, age, ...
- Binary variable encodings, “enumeration encoding”, Fuzzy (Bonarini)
- Use of reals internally: get accurate ranges and thresholds, see if it can be done

What to use as a test problem?

- “Real 6-Multiplexer” (!)
- Boolean 6-multiplexer: Example 011010  $\rightarrow$  0

$$F_6 = b'_0 b'_1 b_2 + b'_0 b_1 b_3 + b_0 b'_1 b_4 + b_0 b_1 b_5$$

- Make “ $RF_6$ ”

$$x = (x_0, \dots, x_5), 0.0 \leq x_i < 1.0$$

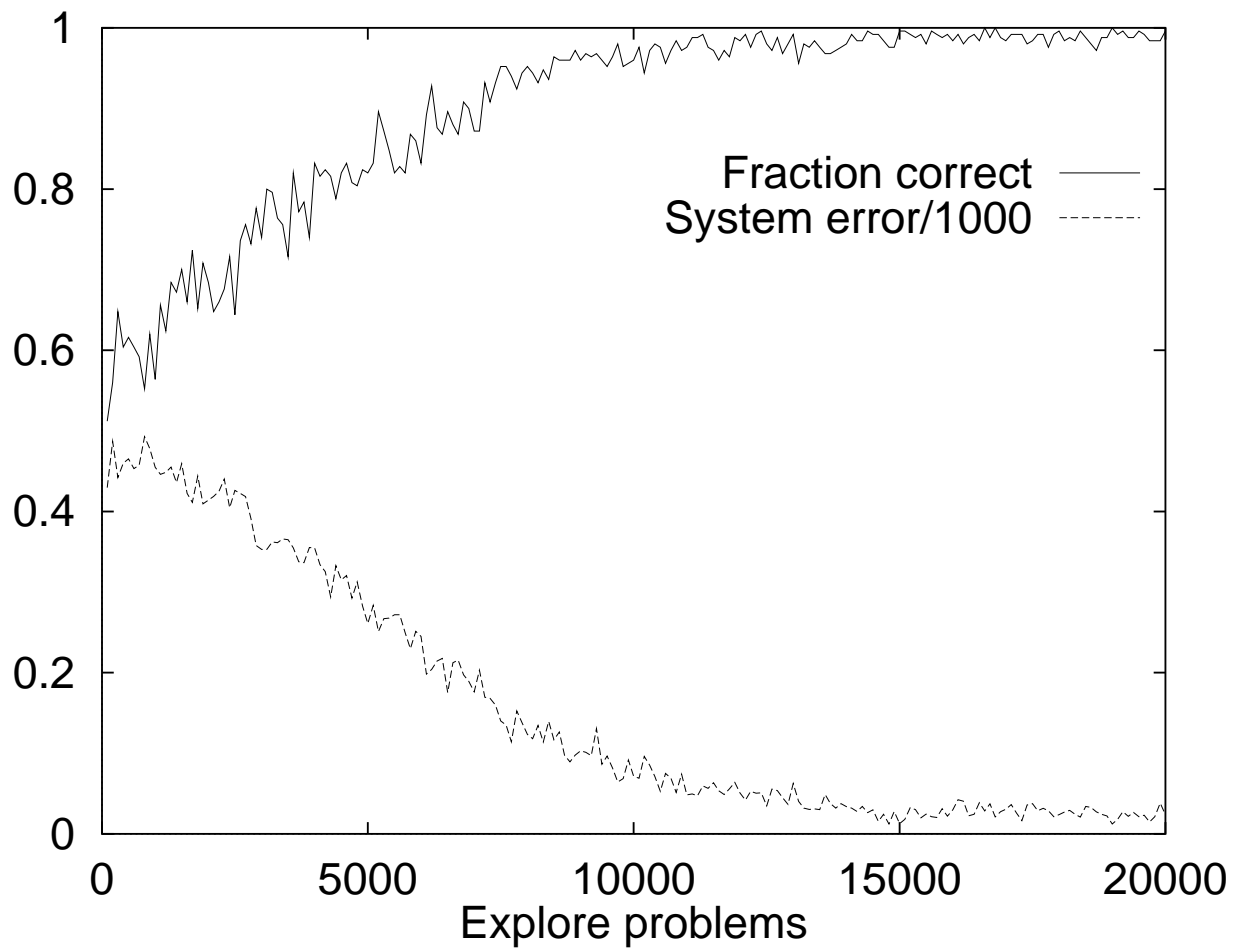
$$\text{Thresholds } 0.0 \leq \theta_i < 1.0$$

Interpret  $x_i$  as 0 if  $x_i < \theta_i$ , else 1; apply  $F_6$

How does XCSR *differ* from XCS?

- Condition consists of “interval predicates”  
 $int_i = (c_i, s_i)$ , so condition =  $(c_0, s_0, \dots, c_5, s_5)$
- Classifier matches iff  $c_i - s_i \leq x_i < c_i + s_i, \forall x_i$
- Mutation adds  $\pm rand(m)$  to allele
- “Covering” creates classifier with condition in which  $c_i = x_i$  and  $s_i = rand(s_0)$

How about an experiment?



Experiment 1, all  $\theta_i = 0.5$

Reward  $R = 1000$  for correct, 0 for incorrect

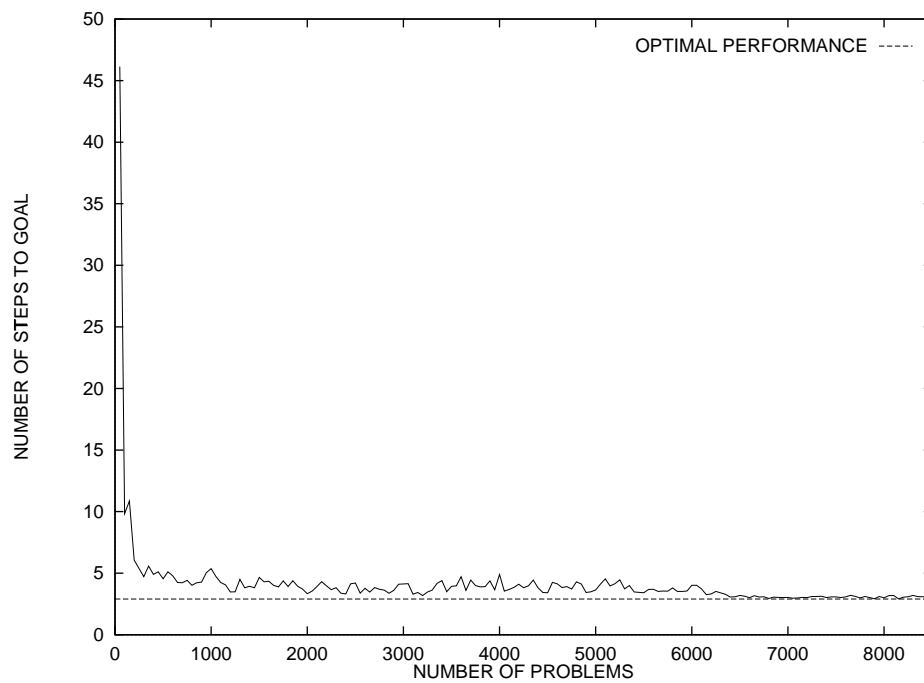
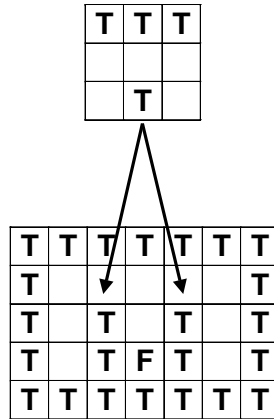
## An action set [A] from Experiment 1

		ACT	PRED	ERR	FITN	NUM
0.	0000000000 ....o0000 0000000000 ....o0000 o000000000 0000000o..	1	0.	.000	14.	1
1.	.....o0000 ....o0000 0000000000 0000000000 o000000000 0000o.....	1	0.	.000	53.	2
2.	.....o0000 ....o0000 0000000000 ....o0000 0000000000 0000o.....	1	0.	.000	40.	1
3.	.....o0000 ....o0000 0000000000 0000000000 o000000000 0000o.....	1	0.	.000	50.	1
4.	.....o0000 ....o0000 0000000000 0000000000 0000000000 0000o.....	1	0.	.000	50.	1
5.	.....o0000 ....o0000 0000000000 0000000000 0000000000 0000o.....	1	0.	.000	140.	3
6.	.....o000o 00000o.... 0000000000 0000000000 0000o..... 0000000000	1	34.	.081	5.	2
7.	.....o00000 ....o0000 0000000000 000000o... 0000000000 0000o.....	1	0.	.000	56.	2
8.	.....o0000 ....o0000 0000000000 ....o00000 0000000000 0000o.....	1	0.	.000	41.	1
9.	.....o00000 ....o0000 0000000000 ....o0000 0000000000 0000o.....	1	0.	.000	58.	1
10.	.....o0000 ....o0000 0000000000 ....o0000 0000000000 0000o.....	1	0.	.000	46.	1
11.	.....o0000 ....o0000 0000000000 ....o00000 0000000000 0000o.....	1	0.	.000	85.	2
12.	.....o0000 ....o0000 0000000000 ....o0000 0000000000 0000o.....	1	0.	.000	43.	1

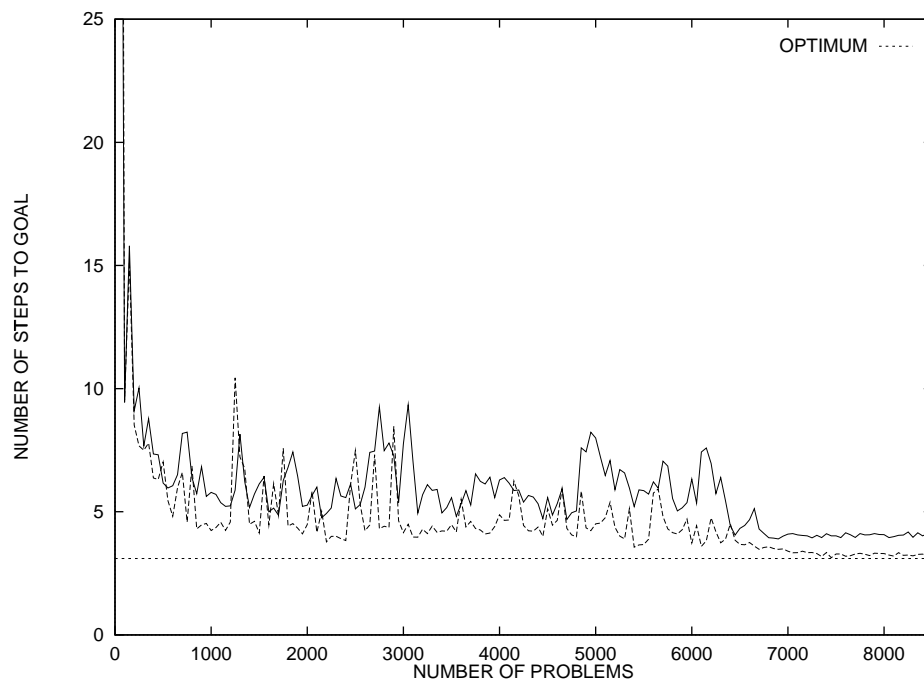
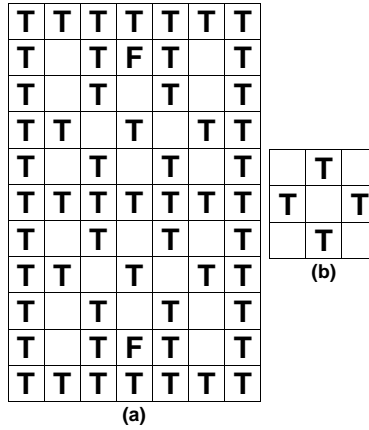
		ACT	PRED	ERR	FITN	NUM
0.	.572,.985 .924,.393 .322,0.99 .948,.417 .818,.812 .331,.404	1	0.	.000	14.	1
1.	.786,.264 0.89,.364 .602,0.99 0.23,.884 .796,.769 .228,.268	1	0.	.000	53.	2
2.	.794,.264 0.89,.364 .262,0.99 .868,.344 .665,.769 .228,.268	1	0.	.000	40.	1
3.	.794,.264 .807,.262 .602,0.99 0.23,.884 .796,.769 .228,.268	1	0.	.000	50.	1
4.	.794,0.28 .807,.262 .684,0.99 0.23,.884 .717,.769 .228,.268	1	0.	.000	50.	1
5.	.794,.264 .807,.262 .602,0.99 0.23,.884 .717,.769 .228,.268	1	0.	.000	140.	3
6.	.743,.232 .172,.404 .813,.903 0.41,.841 .092,.366 .506,.658	1	34.	.081	5.	2
7.	.775,.332 .807,.262 .476,.687 .275,.344 .716,.874 .205,.233	1	0.	.000	56.	2
8.	.786,.264 .807,.262 .288,0.99 .818,.322 .717,.783 .181,.269	1	0.	.000	41.	1
9.	.798,.357 0.89,.364 .247,0.99 .894,.344 .665,.732 .207,.233	1	0.	.000	58.	1
10.	.798,.264 0.89,.364 .247,0.99 .894,.344 .665,.732 .207,.269	1	0.	.000	46.	1
11.	.798,.264 .807,.262 .288,0.99 .818,.322 .717,.783 .207,.269	1	0.	.000	85.	2
12.	.798,.264 .807,.262 .288,1.0 .818,.274 .717,.783 .207,.269	1	0.	.000	43.	1

Input  $\vec{x} = (0.72, 0.55, 0.33, 0.57, 0.14, 0.27)$   
 Boolean interpretation: 110100

## Woods101 (= McCallum's Maze)



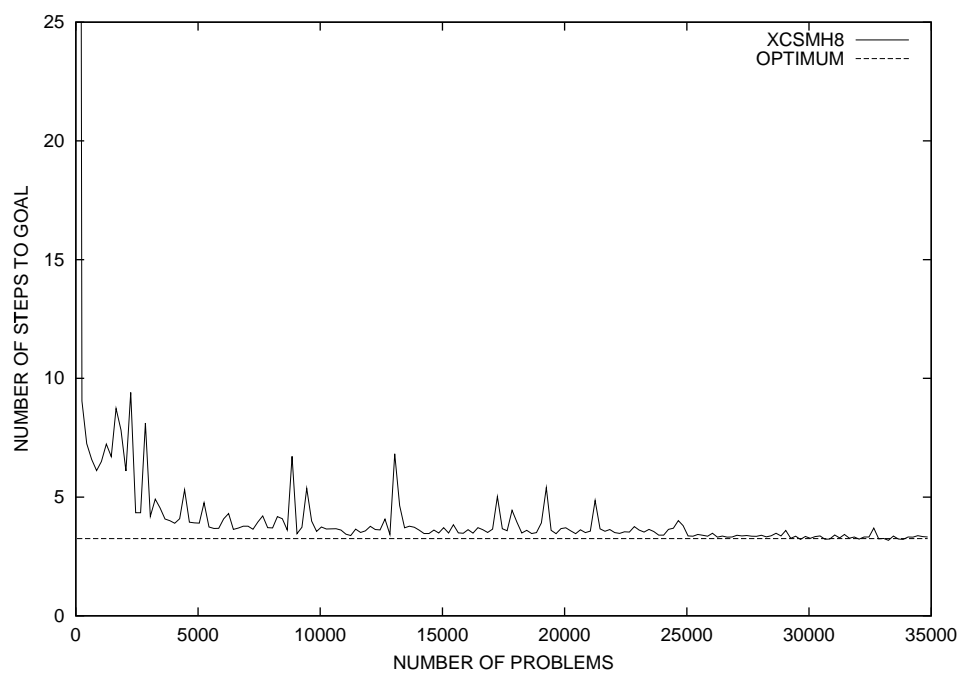
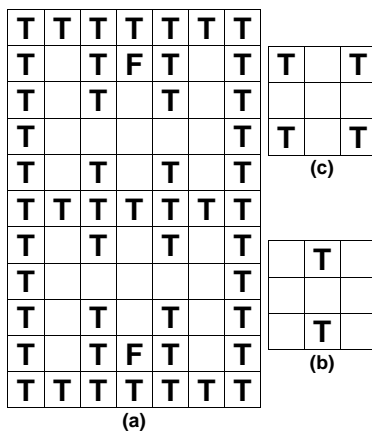
## Woods101.5



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



# Woods102



Uses 8-bit register.

## How is XCS different from other RL systems?

Rule-based, not PDP ("parallel distributed processing")

- Structure is created as needed
- Learning may often be faster because classifiers are inherently non-linear
- Learning complexity may be less than most PDP's
- Classifiers can keep and use statistics; difficult in a network
- Can "see the knowledge"
- Hierarchy and reasoning may be easier, since knowledge is in the form of rules