Condition–action rules in controlling complex systems

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Introduction

- Rules as in a IF <**condition**> THEN <**action**> expression
  - e.g., IF *red AND octagon* THEN *stop-sign*
- Learning Classifier Systems (LCS) – build on such rules
  - learning component (reinforcement, supervised)
  - discovery component (Genetic Algorithms (GAs))
- Control: direct a n/w from any state to a target state
- **Aim:** evolve classifiers (rules+) to control complex systems
  - **single-step** problems – one decision to make
  - **multi-step** problems – series of actions, continuous decisions

Outline

Overall challenge

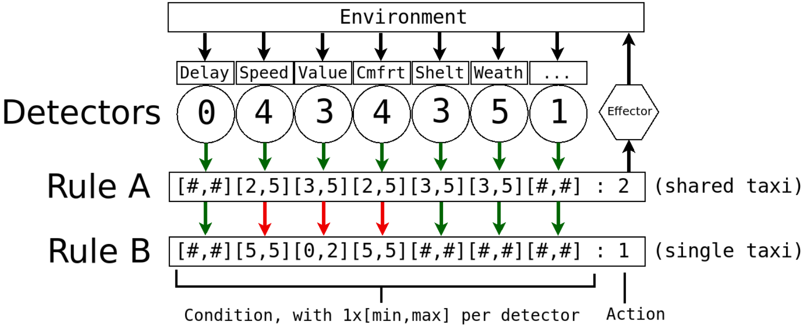
- Input:
  - environment factors:
    - train, taxi, tube, boat and bus [**0 or 5**]; weather [**0 to 5**]
  - journey-specific factors:
    - current delay, delay on current mode(s), onward delay [**0 or 5**]
  - passenger preferences:
    - value, speed, comfort, shelter [**0 to 5**]
- Output:
  - "Correct" single integer recommendation:
    - no change (**0**), single taxi (**1**), shared taxi (**2**), bus (**3**), boat (**4**), tube (**5**), train (**6**)

Population of Rules (the Knowledge)

Condition	:	Action
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [#,#] [2,5] [#,#] [#,#]	:	1
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [2,5] [#,#] [#,#] [#,#]	:	1
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [#,#] [4,5] [#,#] [#,#]	:	1
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [4,5] [#,#] [#,#] [#,#]	:	1
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [0,1] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [2,3] [0,1] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [2,3] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [0,1] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [2,3] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [0,1] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [0,1] [4,5] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [2,3] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [2,3] [4,5] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [4,5] [0,1] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [4,5] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [4,5] [4,5] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [0,1] [0,1] [#,#] [#,#]	:	3
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [0,1] [0,1] [#,#] [#,#]	:	3
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [2,3] [0,1] [#,#] [#,#]	:	3
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [0,1] [0,1] [#,#] [#,#]	:	3
...	:	...

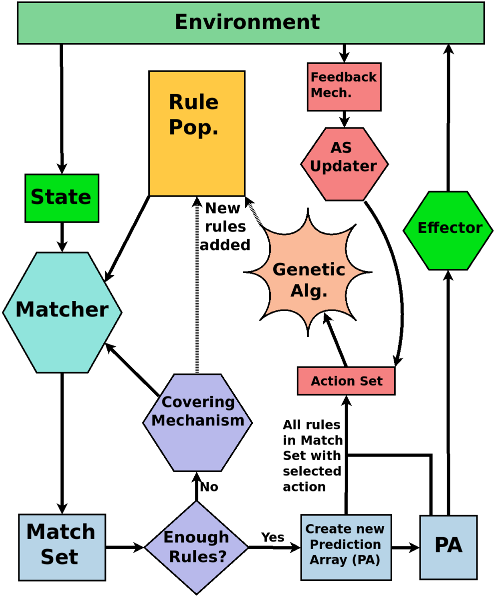
Rule Matching

Figure 1: Simple rule matching example



Karlsen, M.R., Moschoyiannis, S. "Learning condition-action rules for personalised journey recommendations" In RuleML + RR 2018, LNCS 11092, pp.293-301, 2018

Figure 2: XCSI overview



Effector and Feedback Mechanism

- Effector outputs:
  - no change (**0**), single taxi (**1**), shared taxi (**2**), bus (**3**), boat (**4**), tube (**5**), train (**6**)
- Feedback Mechanism, receives:
  - 1000 for a correct suggestion
  - 0 for an incorrect suggestion
- This feedback is used to update the action set rules

Butz, M.V., and Wilson, S.W. "An algorithmic description of XCS." International Workshop on Learning Classifier Systems. Springer, Berlin, Heidelberg, 2000.

Experiments

- Simulation based on London tube network
- 300 artificial ‘passengers’ with randomised:
  - preferences [0 to 5]
  - origin location / station
  - destination location / station
- Each passenger takes multiple journeys

Simulation details (1)

- Random starting time step (0 to 99) for each passenger
- Each time step has weather [0 to 5; random]
- Train, boat, bus and taxi [0 or 5; random]
- Passenger is at one node each time step
- In each time step 5% of links are out-of-action
- Interleaved... (see next 3 slides)

Simulation details (2)

Figure 3: Input list production, step 1 – order

Time Step	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	…
Journey 1	S	S	S	S	S	S											
Journey 2		S	S	S	S	S	S	S	S								
Journey 3					S	S	S	S	S	S	S	S	S	S	S	S	
Journey 4	S	S	S	S	S	S	S	S									
Journey 5			S	S	S	S	S										
Journey 6							S	S	S	S	S	S	S	S	S		
Journey 7	S	S	S	S	S												

S = ‘journey state’

Simulation details (3)

Figure 4: Input list production, step 2 – shuffle

Time Step	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	…
Journey 3					S	S	S	S	S	S	S	S	S	S	S	S	
Journey 1	S	S	S	S	S	S											
Journey 7	S	S	S	S	S												
Journey 6							S	S	S	S	S	S	S	S	S		
Journey 4	S	S	S	S	S	S	S	S									
Journey 2		S	S	S	S	S	S	S	S								
Journey 5			S	S	S	S	S										

S = ‘journey state’

Simulation details (4)

Figure 5: Input list production, step 3 – obtain input vectors

Time Step	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15 …
Journey 3					S	S	S	S	S	S	S	S	S	S	S	S
Journey 1	I1	I4	I8	S	S	S										
Journey 7	I2	I5	I9	S	S											
Journey 6							S	S	S	S	S	S	S	S	S	
Journey 4	I3	I6	…	S	S	S	S	S								
Journey 2		I7	S	S	S	S	S	S	S							
Journey 5			S	S	S	S	S									

S = ‘journey state’

IX = ‘Input X’

Simulation details (5)

Input is checked against the ‘real world’ preferences of the simulated customers to get a correct input output pair...

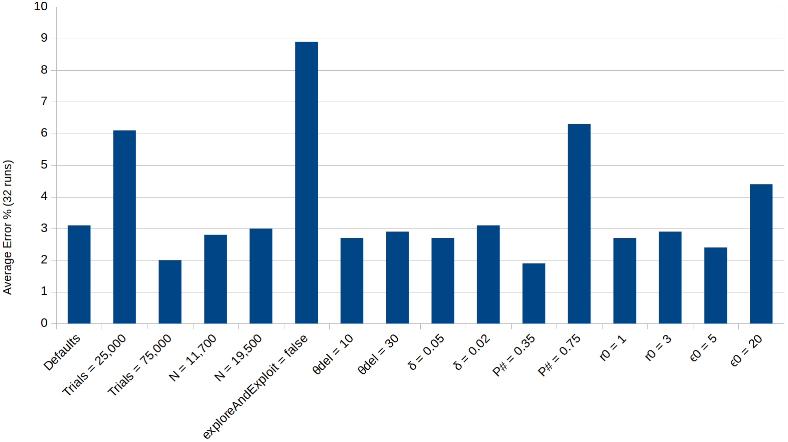
Condition	:	Action
(0)(0)(0)(5)(5)(3)(2)(5)(1)(0)(3)(4)(4)	:	?
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [2,3] [4,5] [#,#] [#,#] [#,#]	:	1
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [0,1] [0,1] [2,3] [#,#] [#,#]	:	2
[0,0] [0,0] [0,0] [5,5] [5,5] [#,#] [#,#] [5,5] [4,5] [0,1] [0,1] [#,#] [#,#]	:	3
...	:	...

Correct input–output pair in this example: `0005532510344:2`

We therefore assemble a list of inputs and answers ($>$ 51,000) for training and testing XCSI.

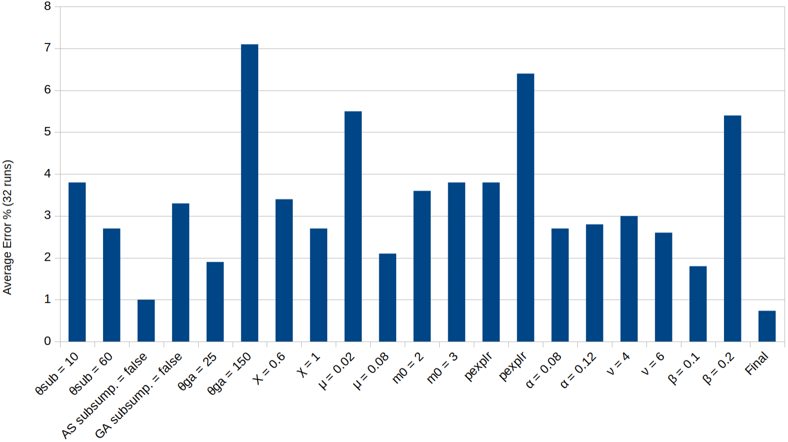
Results (1)

Figure 6: Error % for different parameter settings (1 of 2)



Results (2)

Figure 7: Error % for different parameter settings (2 of 2)



Final Parameters (Adjusted Only)

Parameter	Value	Brief Description
N	11700	Rule population size
$P_{\#}$	0.35	Probability of hash
ϵ_0	5	Error threshold
θ_{ga}	25	Genetic algorithm frequency
θ_{del}	10	Deletion threshold
β	0.1	Affects update of p,ϵ, and action set size for classifiers
α	0.08	Affects fitness updates
ν	6	Affects fitness updates
χ	1	Likelihood of GA crossover operation
μ	0.08	Likelihood of GA mutation operation
δ	0.05	Modifies the effect of fitness on classifier 'deletion vote'
θ_{sub}	60	Subsumption threshold
AS subsumpt.	false	Perform subsumption in the action set?

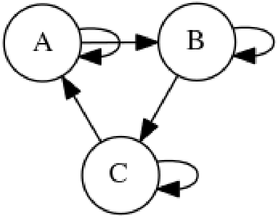
Concluding note

- Headline news: over 99% of passengers would get the correct suggestion
- Real-world problem encoded using condition-action rules
- Rule-based Machine Learning (XCSI) applied to learn passenger preferences and make correct recommendations
  - single-step problem, integer adaptation of the LCS framework

Outline

Random Boolean Networks (RBNs)

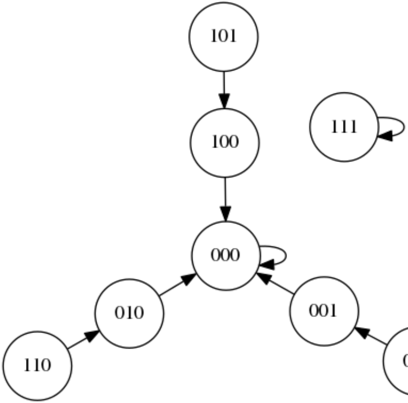
Figure 8: A Random Boolean Network (RBN) with N=3, K=2



Kauffman, S. *The Origins of Order*. Oxford University Press, New York, 1993.

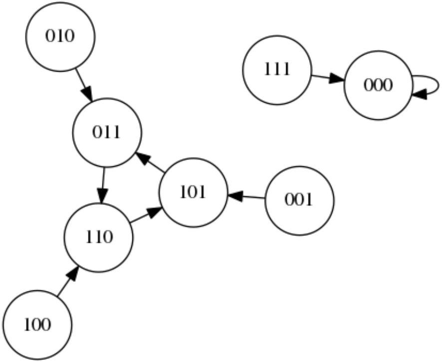
Behaviour of RBNs (1/2)

Figure 9: State space of RBN of Fig. 8 (all AND); two *attractors*



Behaviour of RBNs (2/2)

Figure 10: State space of RBN of Fig. 8 (all XOR); two *atrractors*



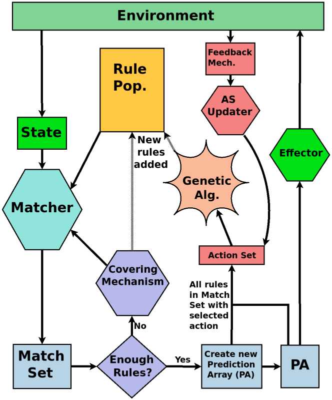
Controllability in RBNs

- The notion of *controllability* in complex networks:
  - the ability to direct a network from any state to a target state
- can take the form:
  - the ability to direct an RBN from any state to (one of) its attractors
- The *objective* is to evolve a rule set that directs an RBN from any state to (one of) its attractors.

Karlsen, M.R., Moschoyiannis, S. Evolution of control with Learning Classifier Systems, *Applied Network Science*, 3(1):1-36, 2018

XCS – overview

Figure 11: XCS - the condition is a ternary string



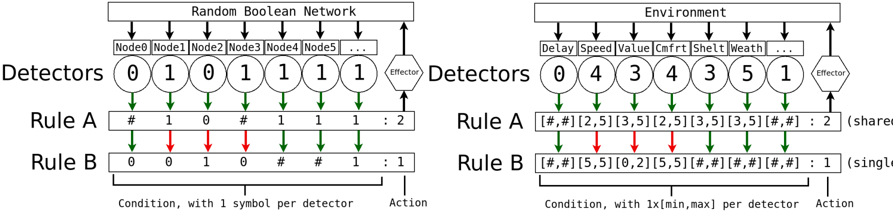
Martin V. Butz and Stewart W. Wilson. "An algorithmic description of XCS." Int'l Workshop on *Learning Classifier Systems*. Springer, Berlin, 2000.

Applying XCS to control RBNs

- Each rule represents a *condition : action* expression that links specific states of the RBN (conditions) to bit flips (actions)
- To shift from single state to the state cycle attractor, apply one of `###:1; ###:2; ###:3`
- To shift from the state cycle to the single state attractor, apply one of `110:3; 011:1; 101:2; 001:3; 010:2; 100:1`
  - where # denotes "don't care" and the action represents the index of the bit to flip

XCS, not XCSI

Figure 12: Rules in XCS (left), and in XCSI (right)



Controlling RBNs using XCS

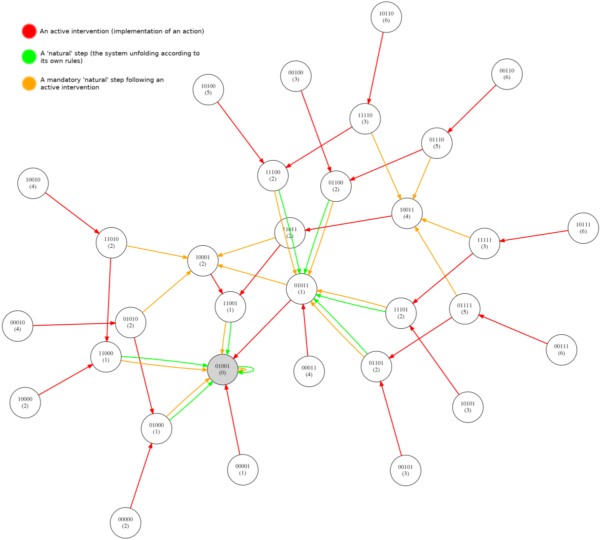


Figure 13: Control graph for a N=5,K=2 RBN using XCS

Outline

System Dynamics Models

- System dynamics models [1] are often understood as complex networks
- *Control* involves interventions on the values of state variables (actions) to steer the network to a desired state
- XCSR (XCS *Real*): real valued extension of XCS
- **Challenge:** Can we use XCSR to identify correct actions on *control nodes* [2] for steering a dynamical system to a desired state ?

[1] Sterman, J.D. *Business Dynamics: Systems Thinking and Modelling for a Complex World*, McGraw-Hill, New York, 2000

[2] Moschoyiannis, S., Elia, N., Penn, A., *et al* "A Web-based Tool for Identifying Strategic Intervention Points in Complex Systems", EPTCS 220:39-52, Elsevier, 2016

Population growth model (1/2)

The *S*-shaped population growth model:

$$\frac{\text{dPopulation}}{\text{dt}} = \text{Birth Rate} - \text{Death Rate} \tag{1}$$

$$\text{Birth Rate} = \text{FractionalBR} * \text{Population} \tag{2}$$

$$\text{Death Rate} = \text{FractionalDR} * \text{Population} \tag{3}$$

$$\text{FractionalBR} = 1 - \frac{1}{1+e^{-7*(\text{PCC}-1)}} \tag{4}$$

$$\text{PCC} = \frac{\text{Population}}{\text{Carrying Capacity}} \tag{5}$$

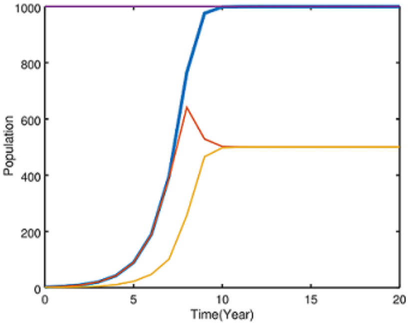
and the value of Carrying Capacity is a constant.

[1] Sterman, J.D. *Business Dynamics: Systems Thinking and Modelling for a Complex World*, McGraw-Hill, New York, 2000

Population growth model (2/2)

- System has only one state variable, thus one attractor where the rates converge

Figure 14: Population (blue) converges at the value of Carrying Capacity (grey); BirthRate(red) and DeathRate(yellow) converge at half that value



Controlling this model (1/2)

- Establish *continuous* control
  - *Step* defined as the change of value in state variable after one unit of time
- XCSR selects an action before each step
  - Action set: *increase/decrease* Birth- and Death-Rate by a constant or percentage, or no action for a given step
- Set *explore* / *exploit* to allow for 50% chance of selecting random action

Controlling this model (2/2)

XCSR can bring the system to a desired stable state (attractor)

- **But** the evolved rule set contains *overgeneralised* rules (too many #'s)
- **Revisited** reward mechanism – generalisation from mutation only
- **But** when current state is "too far" from desired state => *action chain learning problem*
- **Revisited** notion of *step*: action selection followed by full simulation until convergence

Lotka-Volterra predator–prey model (1/2)

This model is a well known non-linear first order differential equations couple:

$$\frac{\mathrm{dPrey}}{\mathrm{dt}} = \mathrm{Prey} * (\mathrm{PreyBirthRate} - \mathrm{DeathRateperPredator} * \mathrm{Predator}) \tag{6}$$

$$\frac{\mathrm{dPredator}}{\mathrm{dt}} = -\mathrm{Predator}(\mathrm{PredatorDeathRate} - \mathrm{BirthRateperPrey} * \mathrm{Prey}) \tag{7}$$

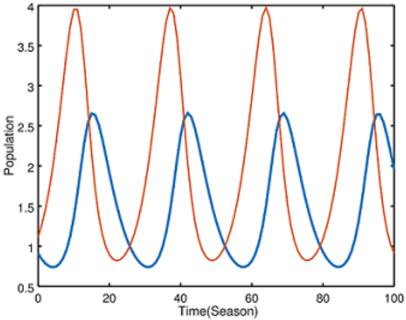
where PreyBirthRate, DeathRatePerPredator, PredatorDeathRate and BirthRatePerPrey are constants.

A.J. Lotka "Elements of Mathematical Biology" Dover Publications, New York, 1956

Lotka-Volterra predator–prey model (2/2)

- System has two state variables, thus more than one attractors

Figure 15: Two state variables imply multiple attractors; Predator(red) and Prey(blue) populations have different attractors



Controlling the L-V model (1/2)

XCSR generates logically correct classifiers, and can bring the system to a desired stable state (attractor)

- **But** when more than 10 consecutive good actions are needed
  - XCSR not able to reach a reward in the early runs
  - overgeneralised rules with prediction of 0 reward
  - hence, these rules are highly accurate, hence their fitness inflated
  - leads to *action chain learning problem*
- **Revisited** notion of action – use adaptive step sizes seems promising

Conclusions

- RBML has traction in controlling complex systems
  - **single-step** problems certainly; caveat: scale
  - **multi-step** problems, continuous control are challenging
- To address the *action chain learning problem*, convert the multi-step problem to multiple single step problems
- **However**, not feasible for higher order systems
  - Try adaptive step sizes => XCSAM
  - Try discretising the system state

Future work (some)

- XCS-Adaptive action Mapping (XCSAM)
- Larger networks, different types of networks (GRNs)
- Different real-world problems, different data
- Dynamic reconfiguration of the network (graph topology)
- optimisation – evolve *optimal control rule sets*
- **Rule-based machine learning** (RBML) is human readable
  - why XCS* suggested a given action, or series of actions
  - how XCS* arrived at the suggestion

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