

Clemens Lode, Urban Richter, Hartmut Schmeck
Karlsruhe Institute of Technology (Germany)
Institute AIFB
July, GECCO 2010

Adaption of XCS to Multi-Learner Predator/Prey Scenarios

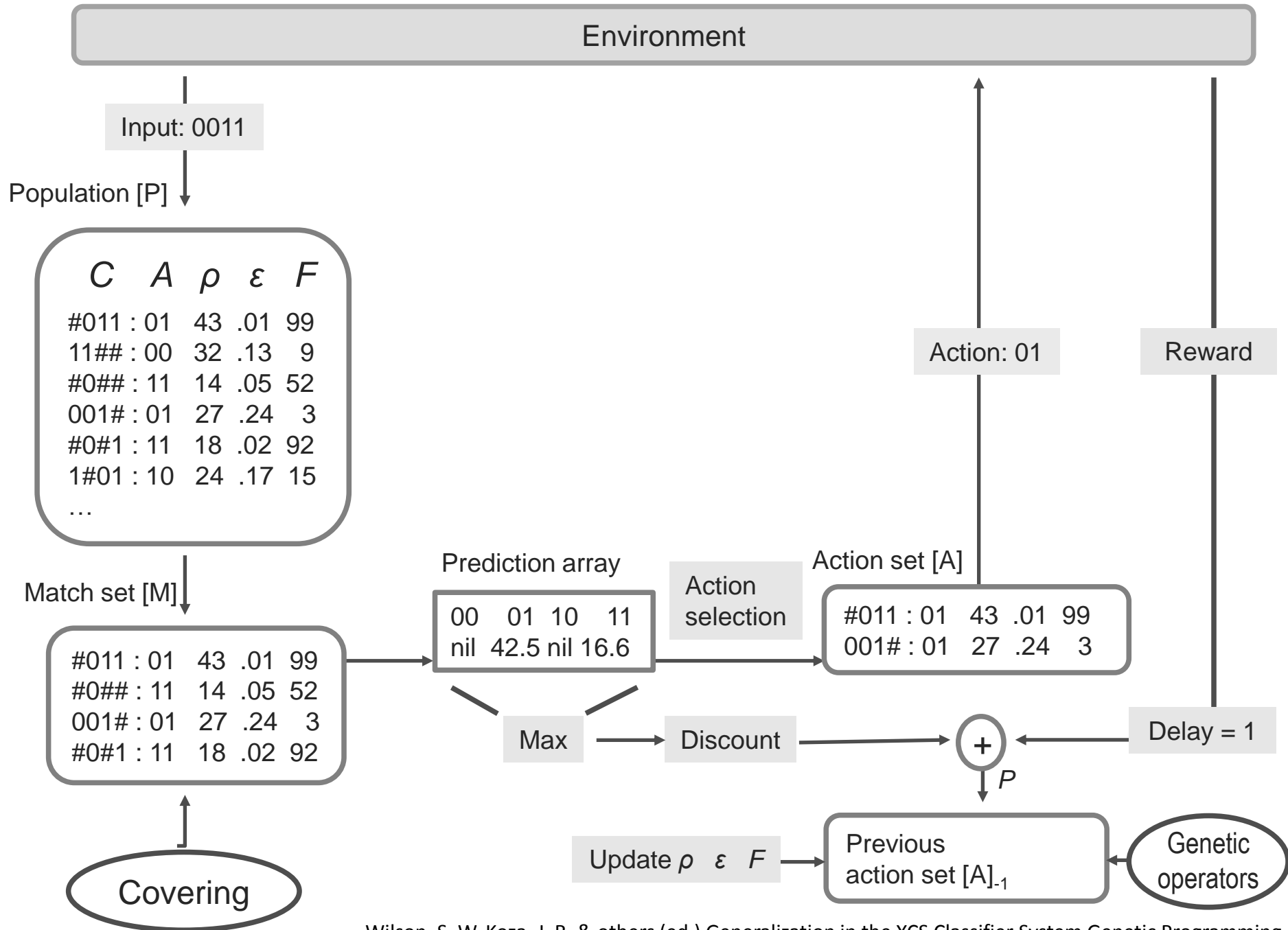


Outline

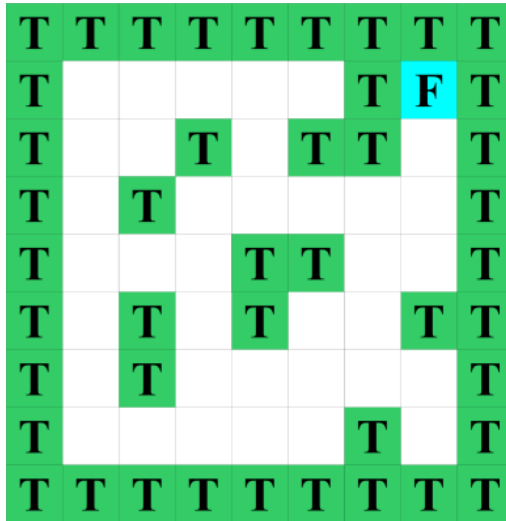


<http://www.flickr.com/photos/yathin>

- Learning Classifier Systems
- XCS in Predator/Prey Scenarios
- Adapting the Reward Function
- Experimental Results



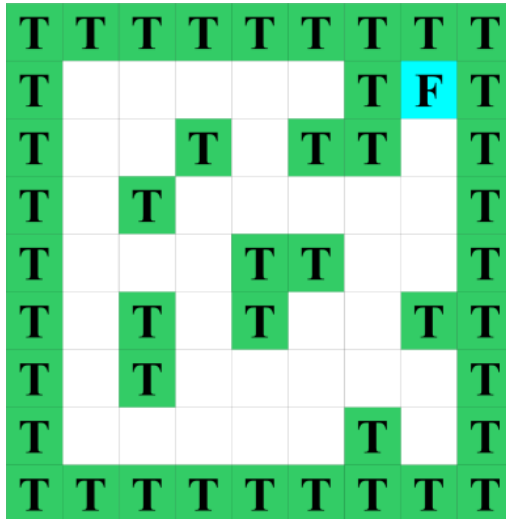
Learning Classifier Systems



T: Tree
F: Food

- Standard (Multi-Step) Problem:
 - Maze6
- Goal:
 - Find shortest path to the food starting from a random point

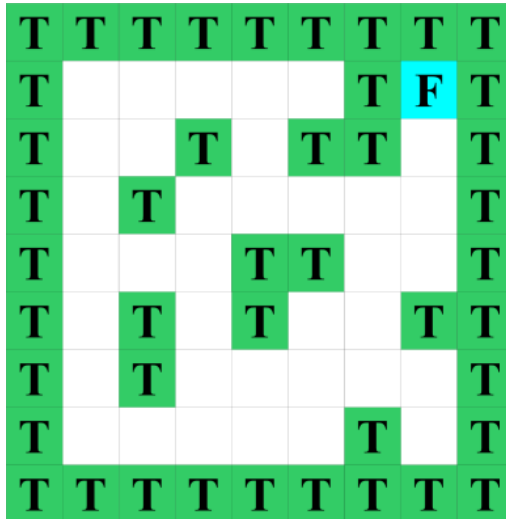
Learning Classifier Systems



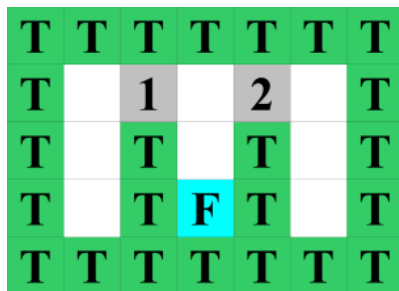
T: Tree
F: Food

- Problem:
 - Limited sensors, no global knowledge
 - Partially observable Markov decision process
- Solution:
 - Iterations, back-propagation of reward

Learning Classifier Systems



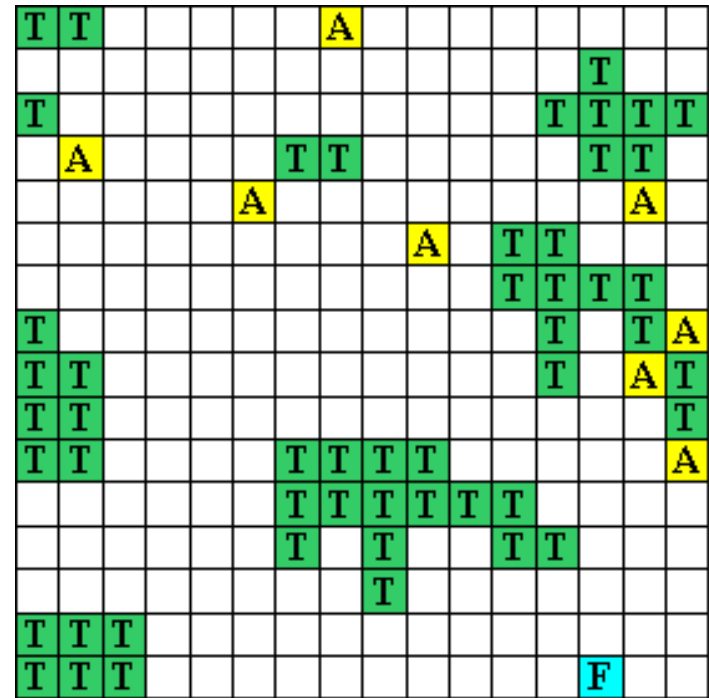
T: Tree
F: Food



- Problem:
 - Limited sensors, no global knowledge
 - Partially observable Markov decision process
- Solution:
 - Iterations, back-propagation of reward
- Aliasing positions:
 - Handle by using memory

Learning Classifier Systems

- Many aliasing positions
- Other agents present
- Dynamic world
 - food and other agents move
- Limited sensors



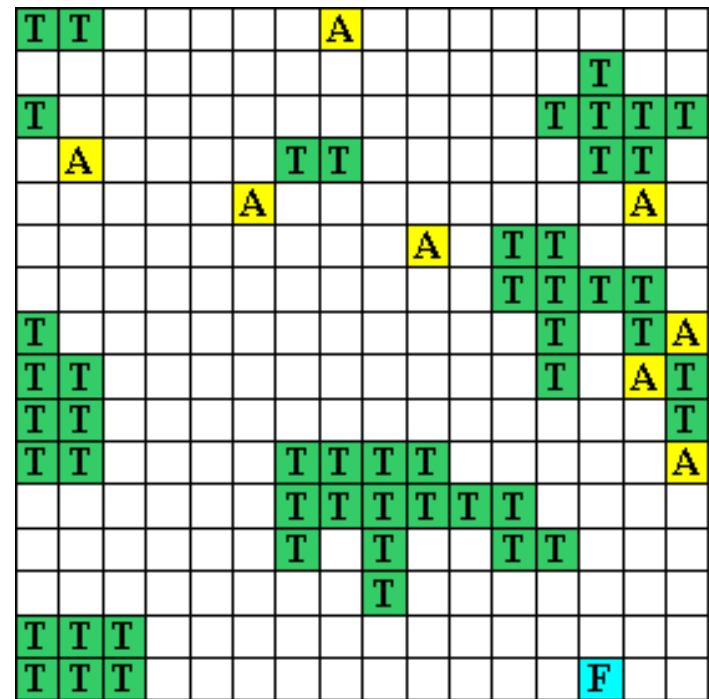
T: Trees

F: Food

A: Agent

Predator/Prey Scenarios

- Terminology:
 - Obstacles, Prey, Predator
- Goal: Get near the moving prey as often as possible
 - Global observation task
 - Continuous
 - Average Quality



T: Trees/Obstacles
F: Food/Prey
A: Agent/Predator

Classification of Predator/Prey Scenarios

- (1) Access to local information only
 - (2) open areas with some obstacles
 - (3) internal state unknown to others
- No standard MDP
 - Limited sensors (1, 3)
 - Aliasing positions (2)

Classification of Predator/Prey Scenarios

- (1) Access to local information only
 - (2) open areas with some obstacles
 - (3) internal state unknown to others
 - (4) dynamic scenario
- No standard MDP
 - Limited sensors (1, 3)
 - Aliasing positions (2)
 - No POMDP
 - Non-static scenario (4)

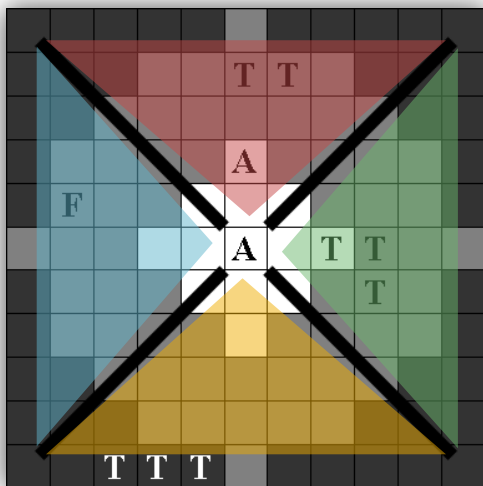
Classification of Predator/Prey Scenarios

- (1) Access to local information only
 - (2) open areas with some obstacles
 - (3) internal state unknown to others
 - (4) dynamic scenario
 - (5) predators share global observation task
 - (6) runs continuously
- No standard MDP
 - Limited sensors (1, 3)
 - Aliasing positions (2)
 - No POMDP
 - Non-static scenario (4)
 - XCS has to be adapted
 - No “final” reward (5), no iterations (6)

Sensors

One sensor array for each direction

N			E			S			W		
A	-	-	-	T	-	-	-	-	-	-	-
-	T	-	-	T	-	-	-	-	-	-	F



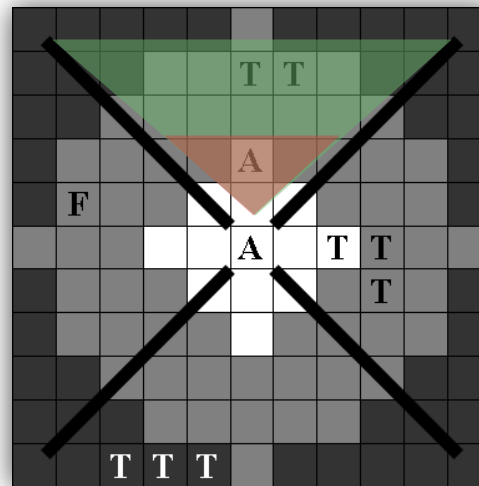
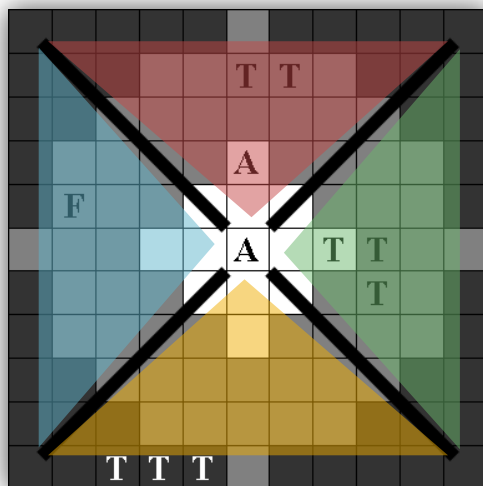
Sensors

One sensor array for each direction

N			E			S			W		
A	-	-	-	T	-	-	-	-	-	-	-
-	T	-	-	T	-	-	-	-	-	-	F

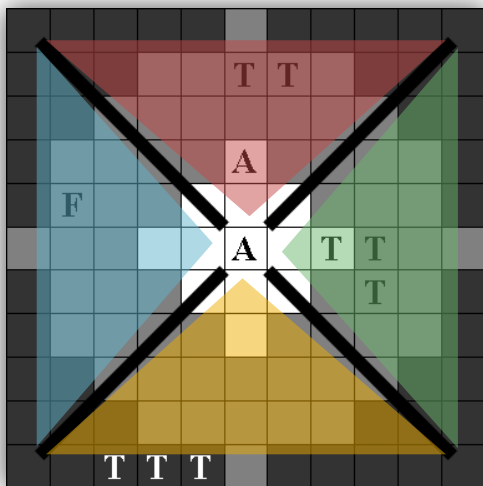
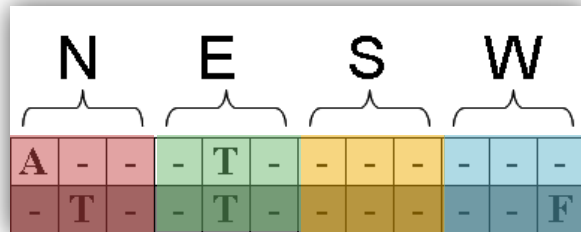
Sensors can sense either far or near

N			E			S			W		
A	-	-	-	T	-	-	-	-	-	-	-
-	T	-	-	T	-	-	-	-	-	-	F

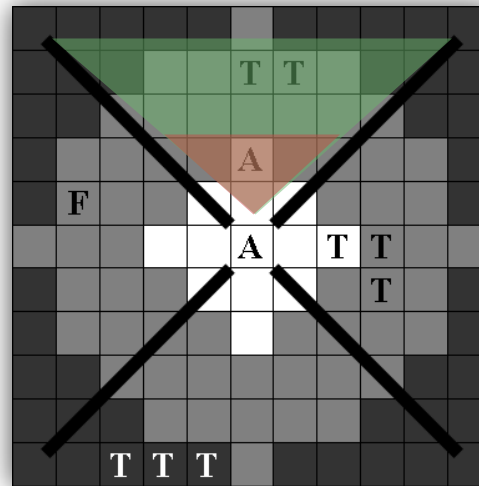
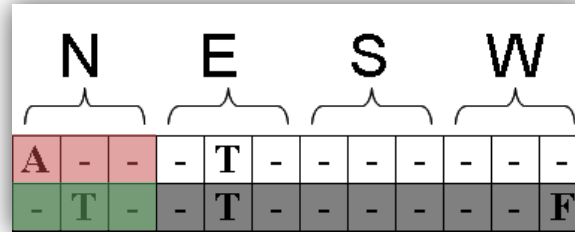


Sensors

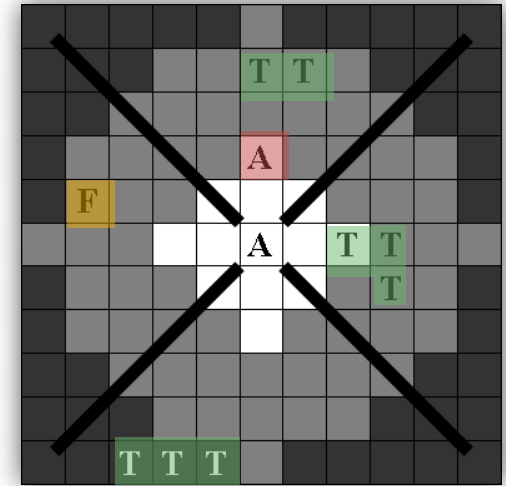
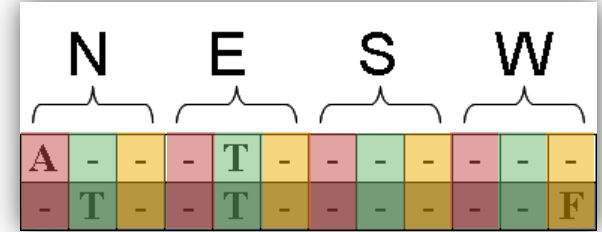
One sensor array for each direction



Sensors can sense either far or near (observation range / sight range)



Sensors can distinguish between Predators, Prey and Obstacles



Adaption of the standard XCS Reward Function

- Standard implementation:
- Adapted implementation

Adaption of the standard XCS Reward Function

- Standard implementation:
 - Reward:
 - Food is in a neighboring cell
- Adapted implementation
 - Reward:
 - Food is in observation range ("XCS obs")
 - Food is in sight range ("XCS sight")

Adaption of the standard XCS Reward Function

- Standard implementation:

- Reward:

- Food is in a neighboring cell

- Action:

- Assign reward
 - Restart scenario
 - Switch between explore/exploit phase

- Adapted implementation

- Reward:

- Food is in observation range ("XCS obs")
 - Food is in sight range ("XCS sight")

- Action:

- Assign reward
 - Continue scenario
 - Always use exploit phase

Classification of Predator/Prey Scenarios

- Global knowledge cannot be reconstructed
 - Memory becomes invalid after each step
- The predator/prey scenario is a Non-observable Markov Decision Processes

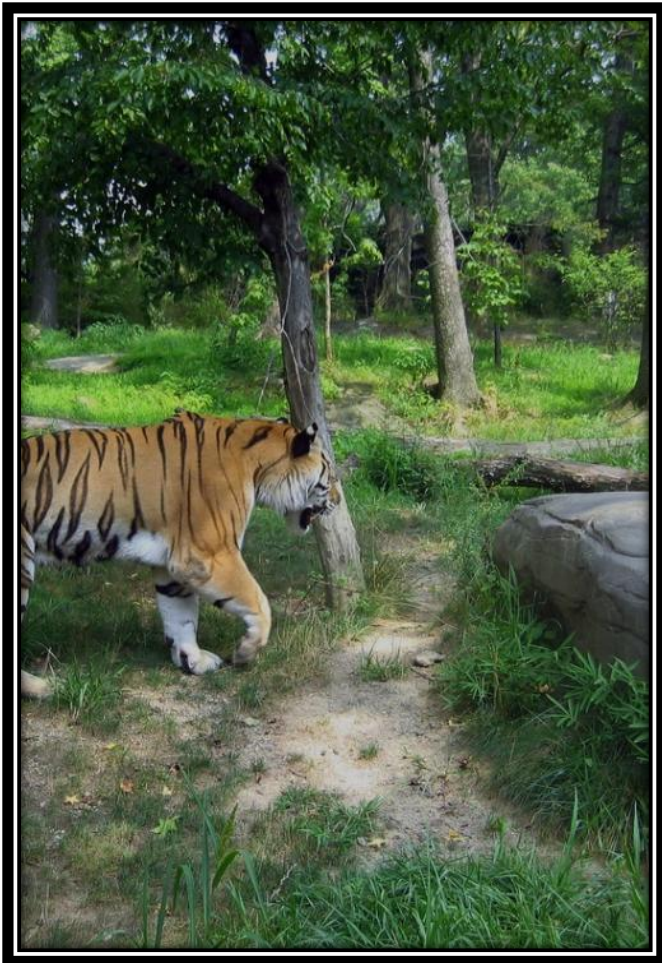
Classification of Predator/Prey Scenarios

- Global knowledge cannot be reconstructed
 - Memory becomes invalid after each step
- The predator/prey scenario is a Non-observable Markov Decision Processes
- Despite being a NOMDP, can the XCS still learn?

Classification of Predator/Prey Scenarios

- Global knowledge cannot be reconstructed
 - Memory becomes invalid after each step
- The predator/prey scenario is a Non-observable Markov Decision Processes
- Despite being a NOMDP, can the XCS still learn?
 - Yes, the prey does move only a limited number of cells
 - The environment does not completely change each turn

Testing Methodology



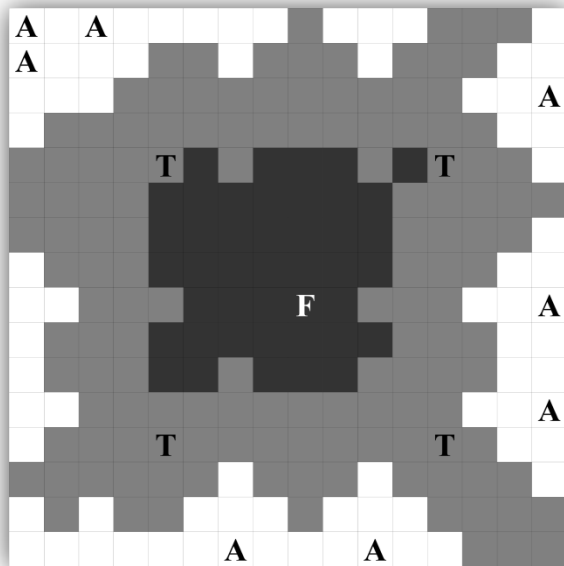
http://www.flickr.com/photos/james_crowley

- “XCS obs”, “XCS sight”
- “Obstacle-evading prey”
- “Predator-evading prey”
- “Blinded Prey”
- Standard XCS parameter settings

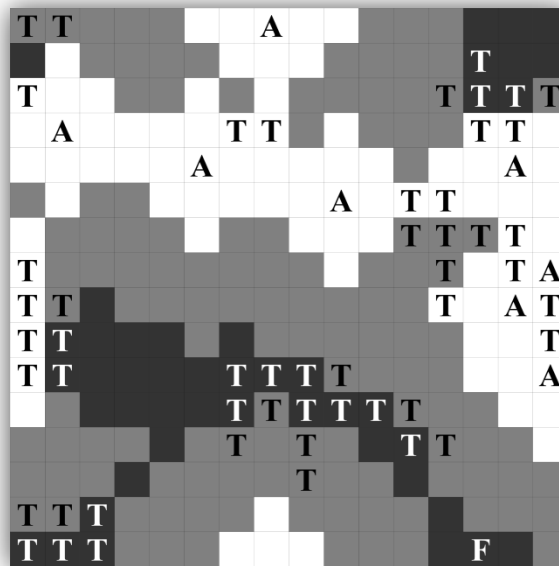
Scenario Configurations

- Three different scenarios with observation and sight ranges

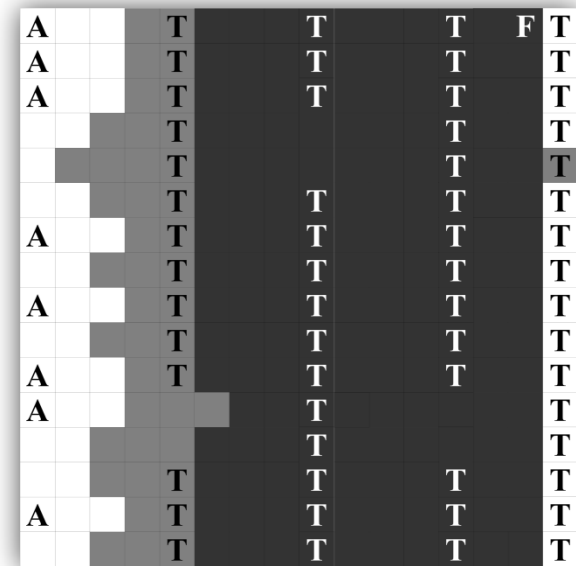
“Pillar scenario”



“Random scenario”



“Difficult scenario”

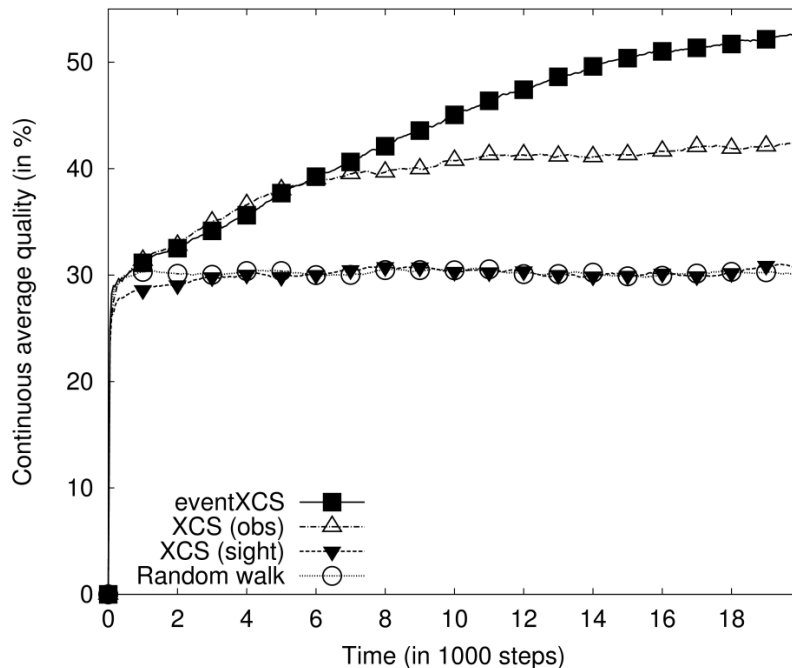


XCS Experimental Results

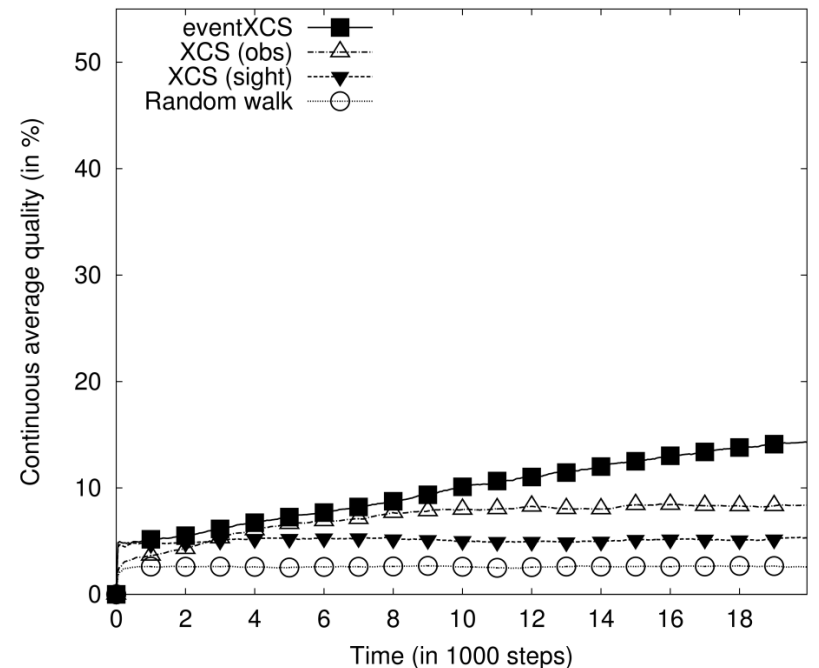
“Pillar Scenario”

- XCS (obs) shows some learning

Obstacle-evading prey



Predator-evading prey

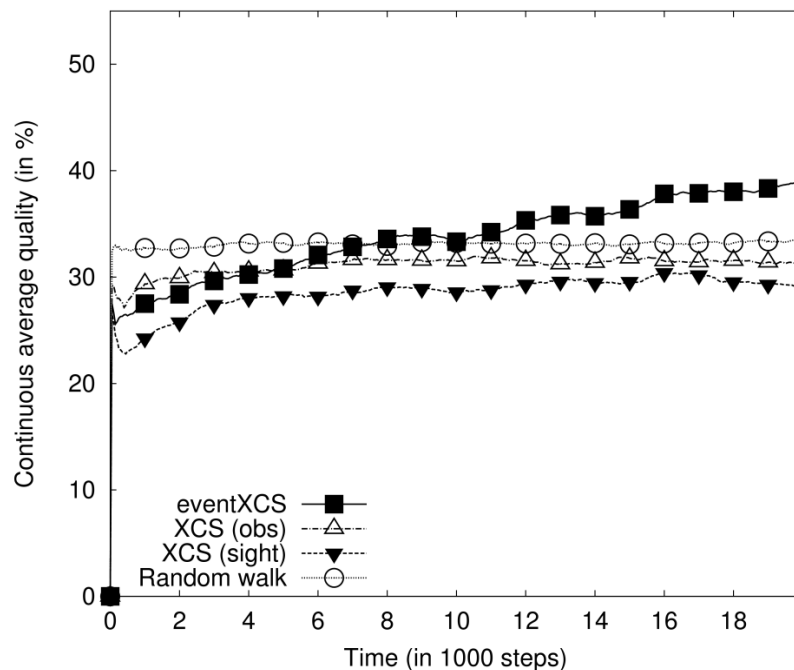


XCS Experimental Results

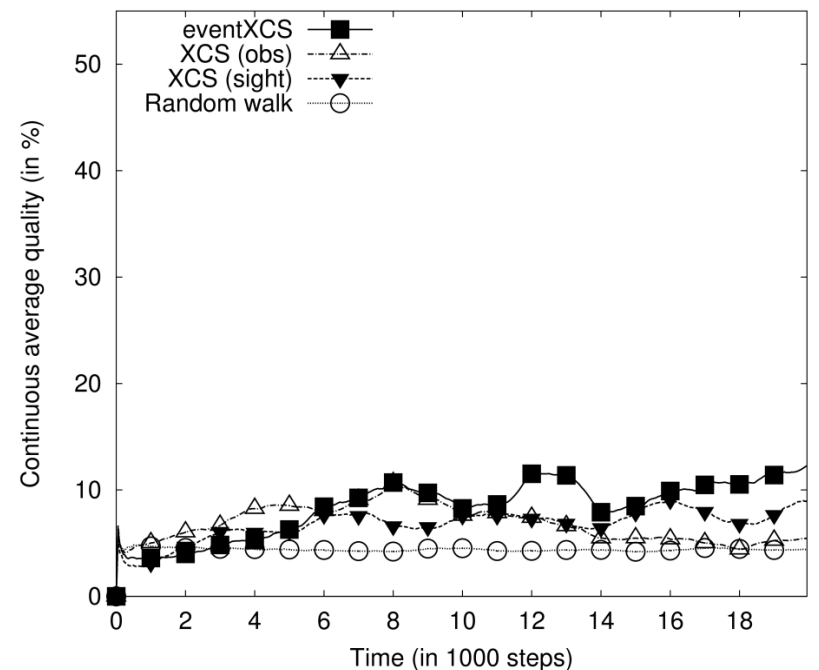
“Random Scenario”

- XCS shows very little learning

Obstacle-evading prey



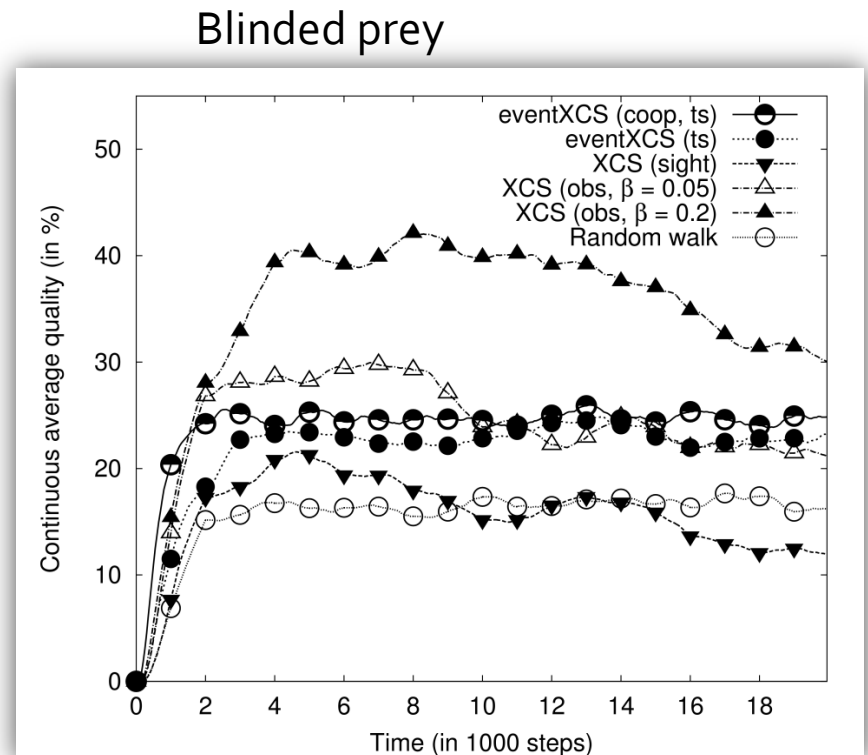
Predator-evading prey



XCS Experimental Results

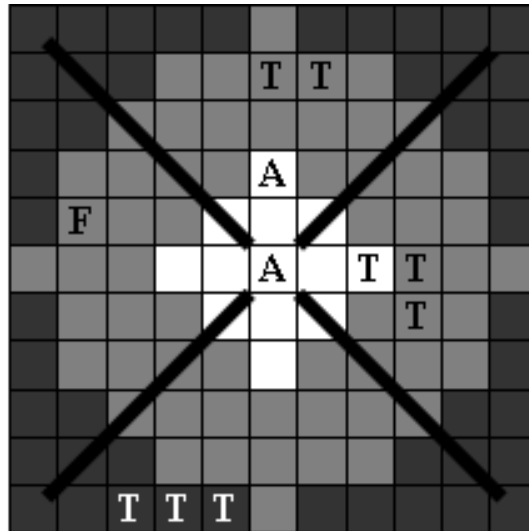
“Difficult Scenario”

- XCS shows significant learning
 - But also unlearning after 8,000 steps
- “Difficult Scenario” is a maze-like scenario, this result was expected



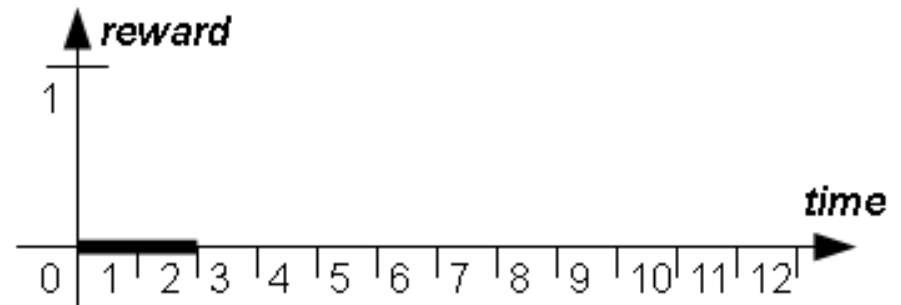
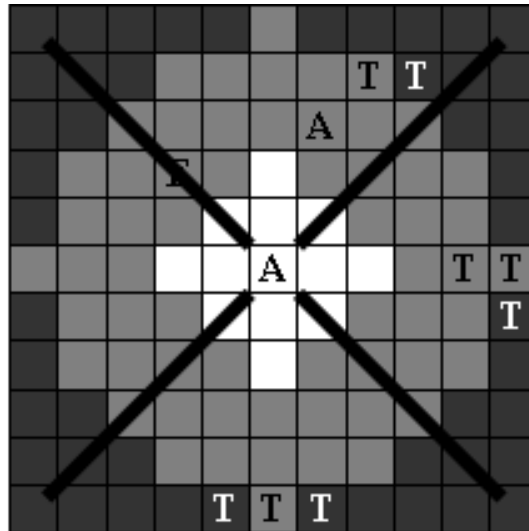
Base Reward and Reward Events

	N	E	S	W
A	1	0	0	0
T	0	1	0	0
F	0	0	0	0
A	0	0	0	0
T	1	1	0	0
F	0	0	0	1



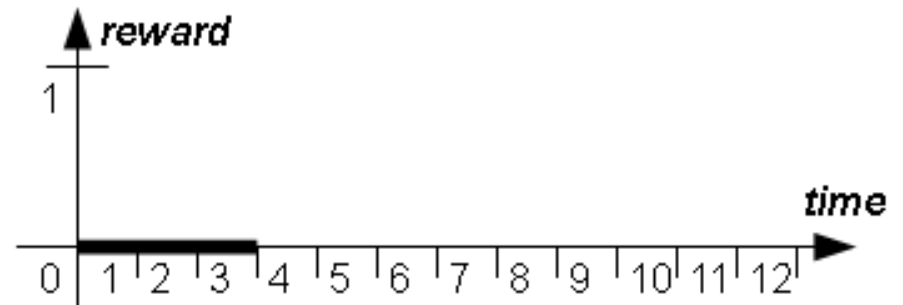
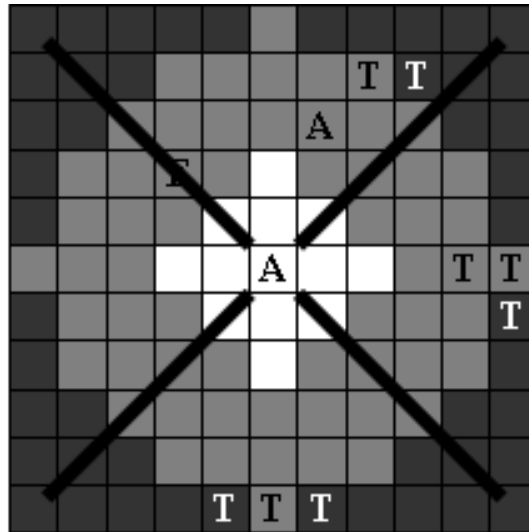
Base Reward and Reward Events

	N	E	S	W
A	0	0	0	0
T	0	0	0	0
F	0	0	0	0
A	1	0	0	0
T	1	1	1	0
F	1	0	0	0



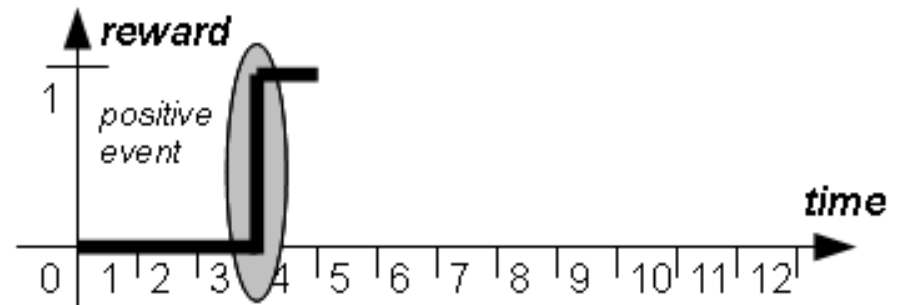
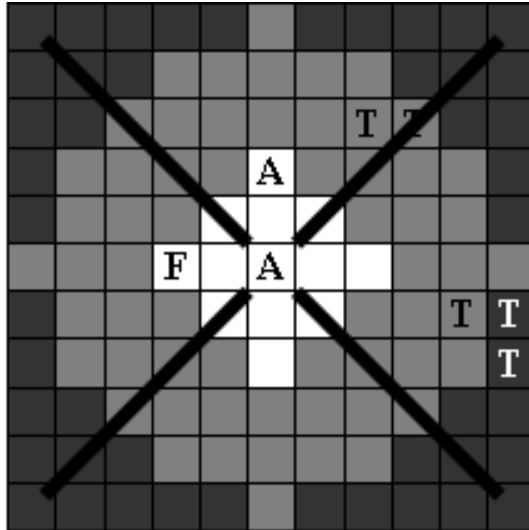
Base Reward and Reward Events

	N	E	S	W
A	0	0	0	0
T	0	0	0	0
F	0	0	0	0
A	1	0	0	0
T	1	1	1	0
F	1	0	0	0



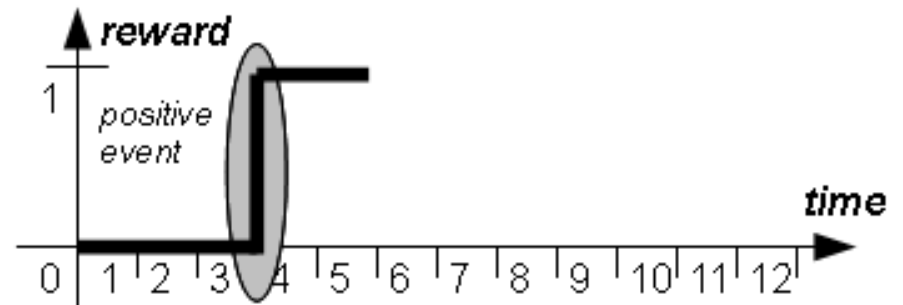
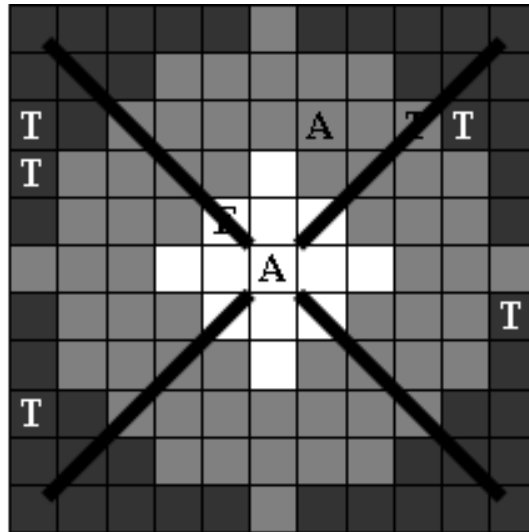
Base Reward and Reward Events

	N	E	S	W
A	1	0	0	0
T	0	0	0	0
F	0	0	0	1
A	0	0	0	0
T	1	1	0	0
F	0	0	0	0



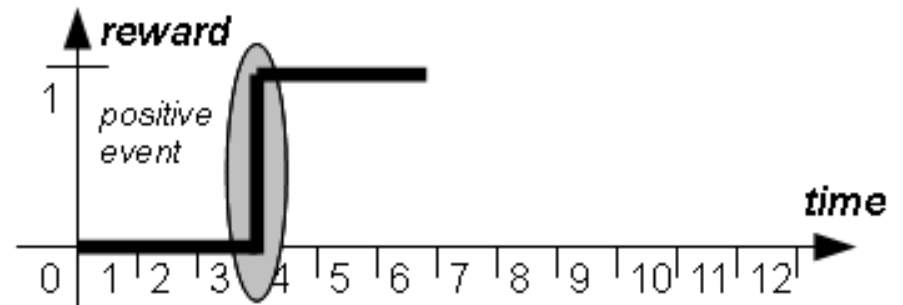
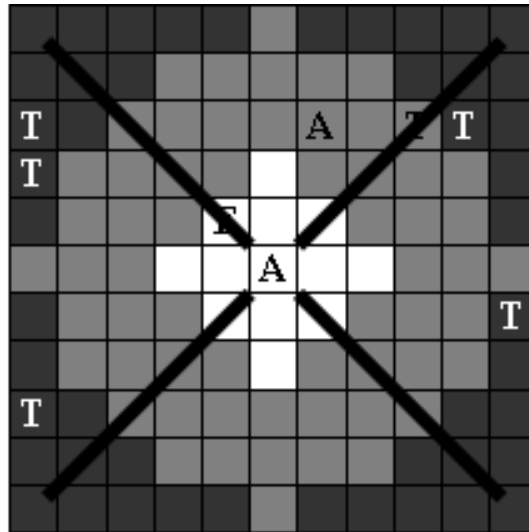
Base Reward and Reward Events

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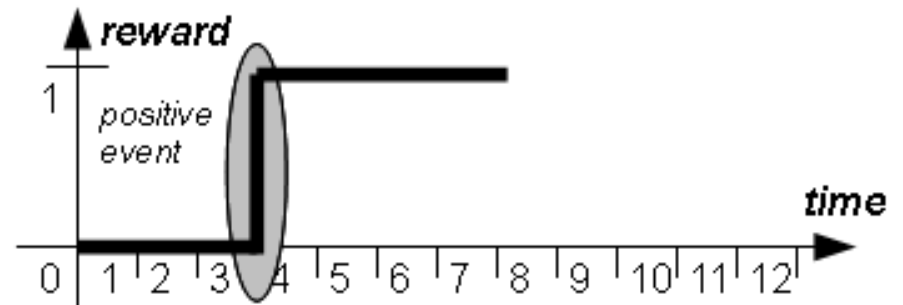
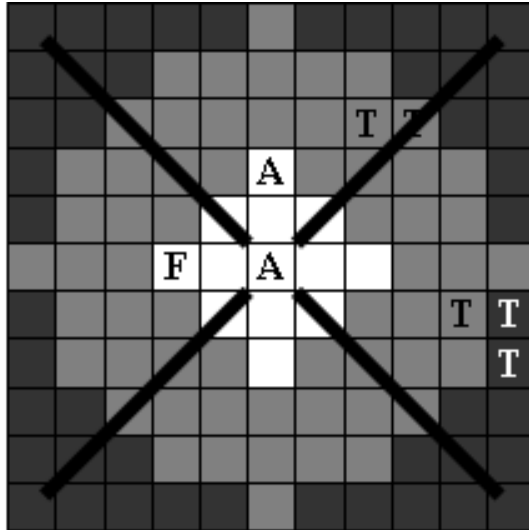
Base Reward and Reward Events

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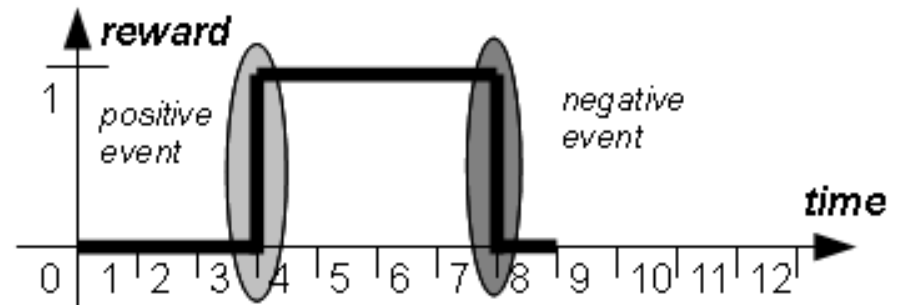
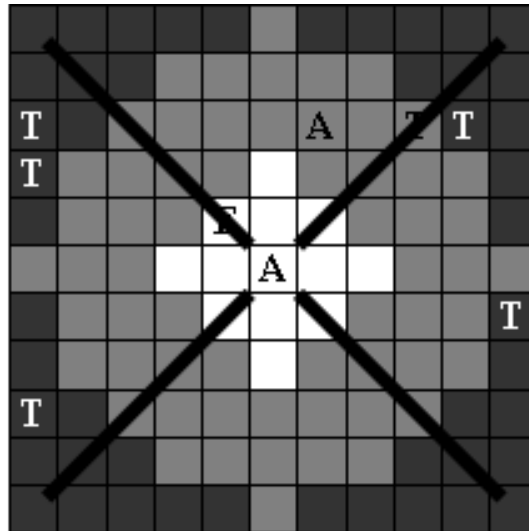
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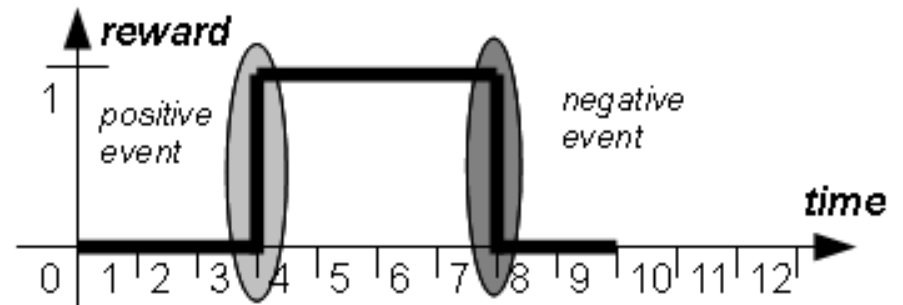
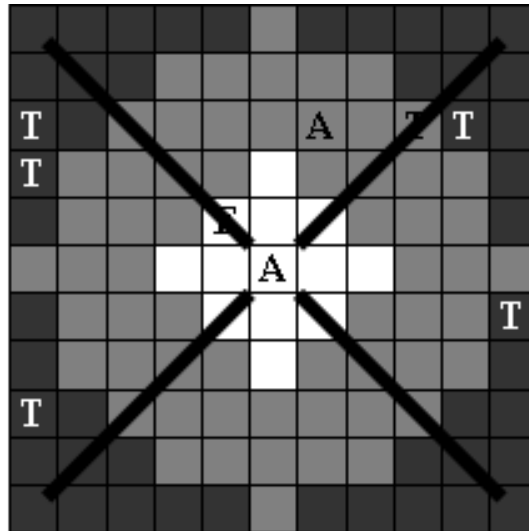
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F	0	0	0	0



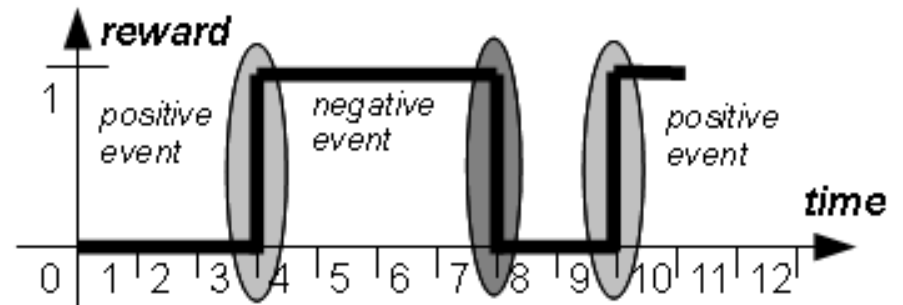
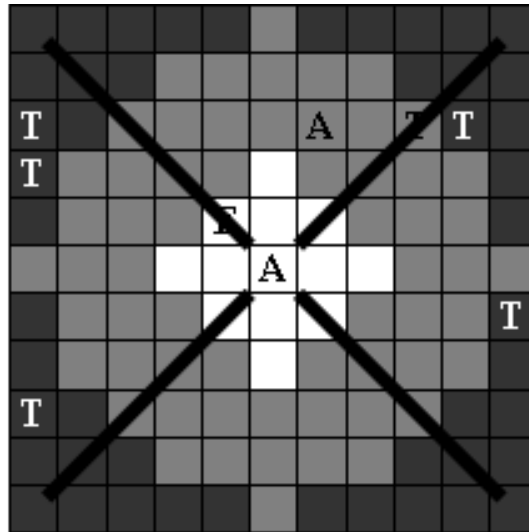
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A	0	0	0	0
T	1	1	0	0
F	0	0	0	0



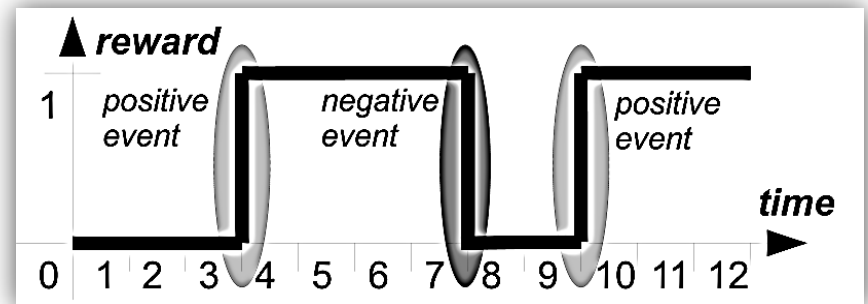
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A	0	0	0	0
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F	0	0	0	0



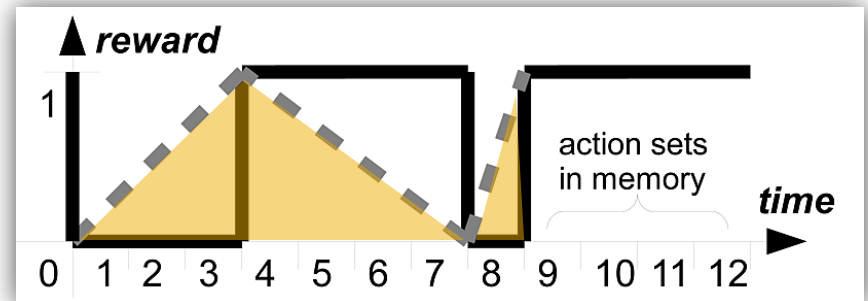
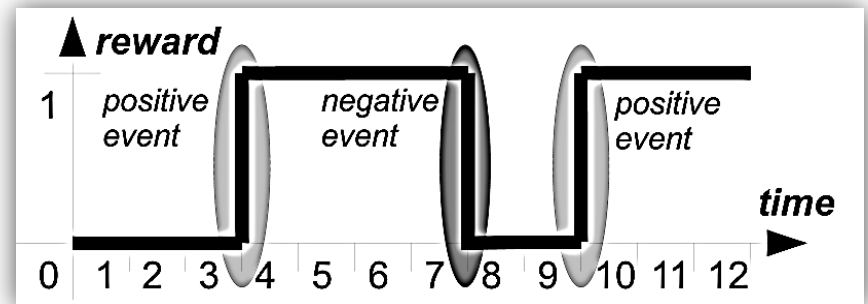
Reward Distribution

- Analyze succession of positive and negative events



Reward Distribution

- Analyze succession of positive and negative events
- Distribute the reward as soon as possible (i.e. at each event)
- Idea:
 - Action sets closer to an event probably contributed more



eventXCS

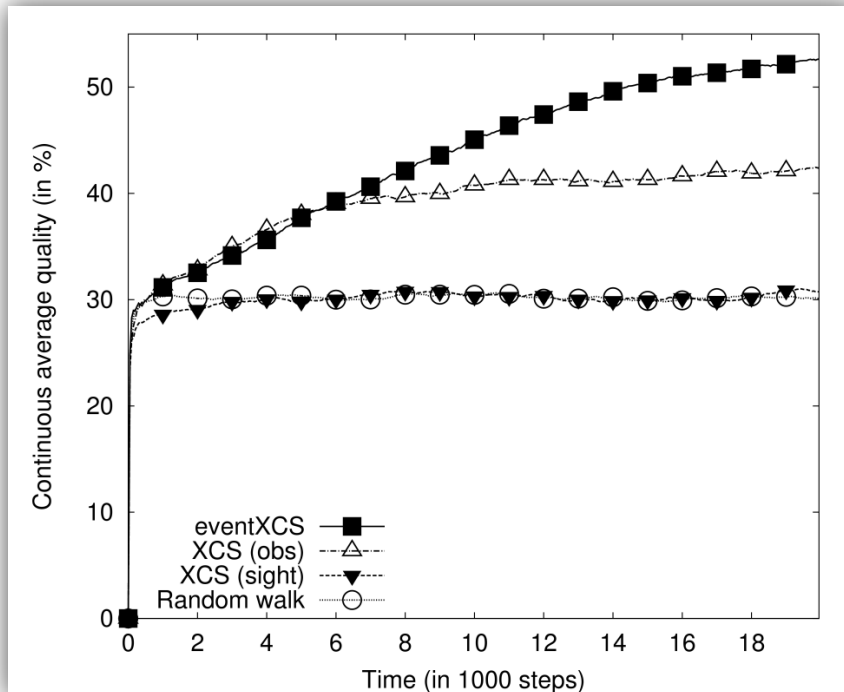
- Adaption of XCS to Multi-Learner predator/prey scenarios
 - “eventXCS”
 - Reward events
 - Reward distribution

eventXCS Experimental Results

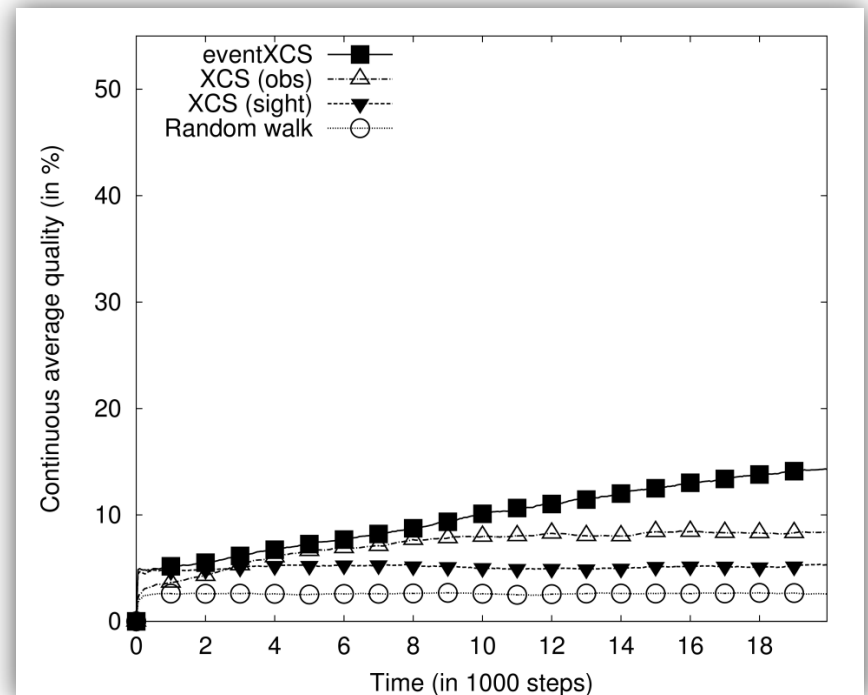
“Pillar Scenario”

- eventXCS clearly outperforms XCS

Obstacle-evading prey



Predator-evading prey

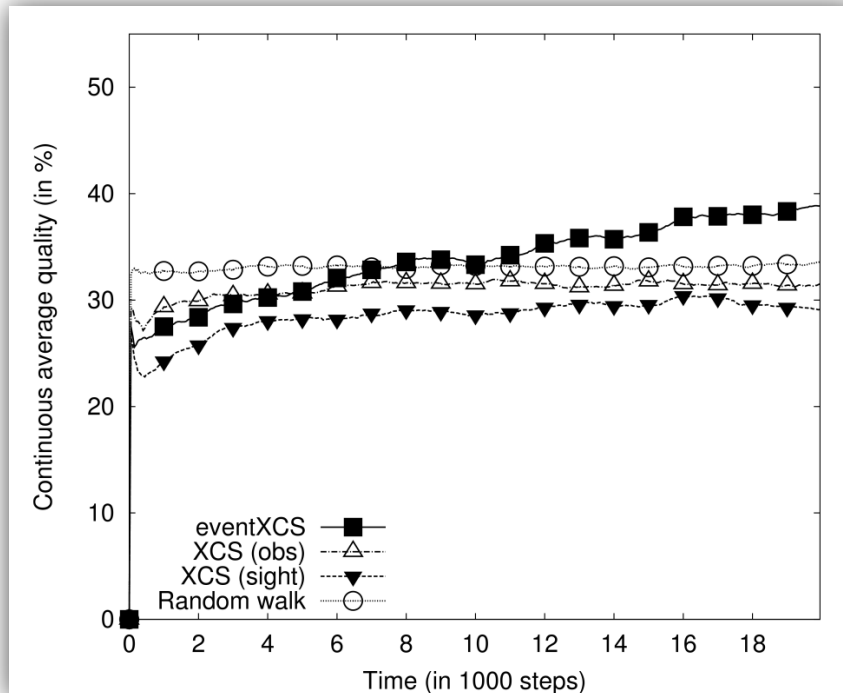


eventXCS Experimental Results

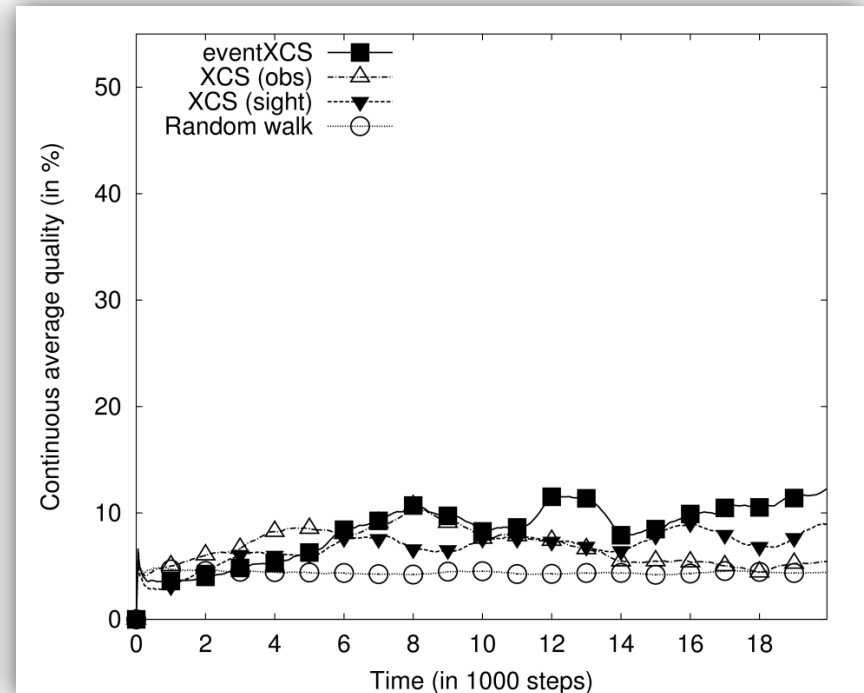
“Random Scenario”

- eventXCS shows slow but steady learning with an obstacle-evading prey

Obstacle-evading prey



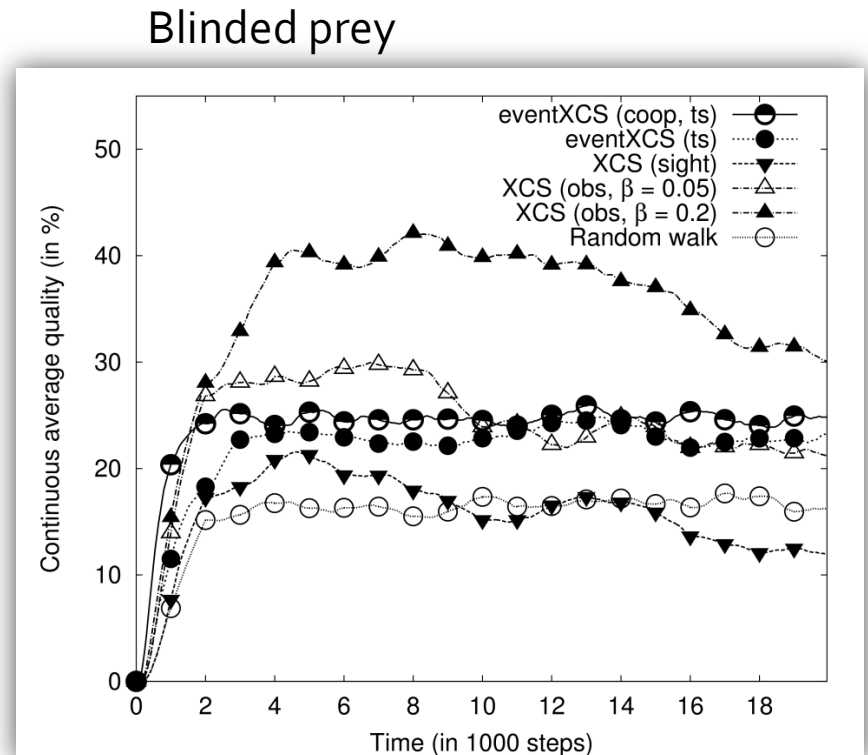
Predator-evading prey



eventXCS Experimental Results

“Difficult Scenario”

- eventXCS fails in this scenario
- Using “tournament selection” it shows acceptable results with no sign of unlearning



Conclusion



Adaption of XCS to Multi-Learner Predator/Prey Scenarios

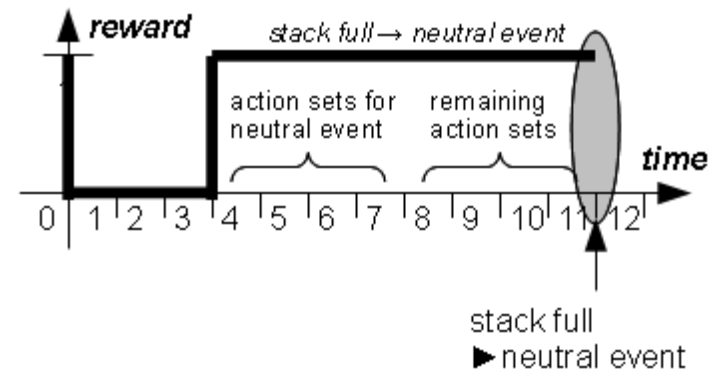


- Thank you for your attendance!

Backup slides

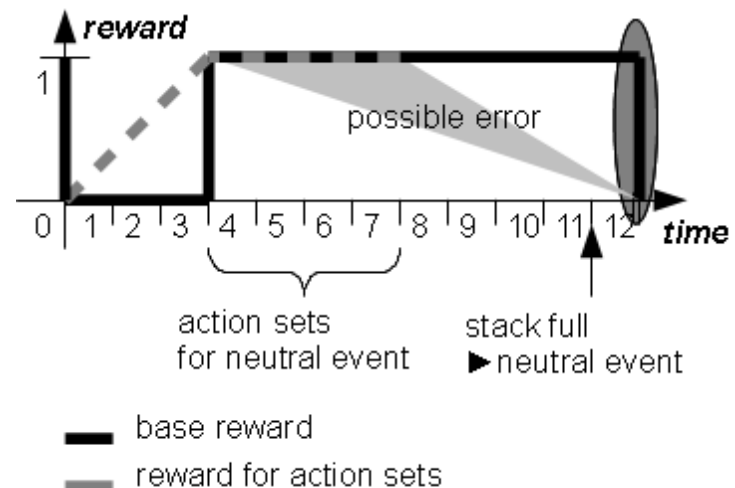
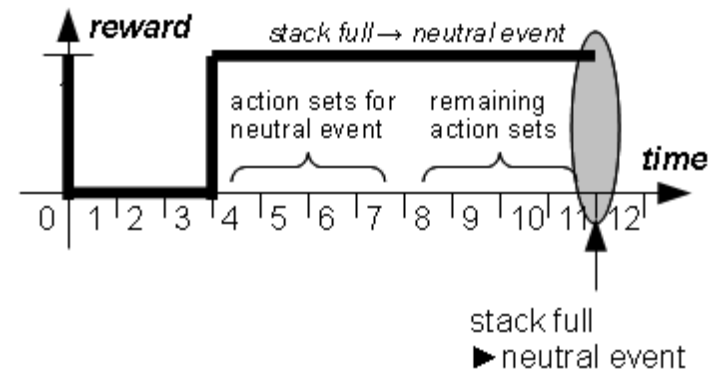
Neutral Events

- Neutral Event
 - No positive or negative event for a number of steps
 - Half of the action sets is discarded and receives reward
 - Idea:
 - Good actions are rewarded earlier
 - Preventing of dead ends



Neutral Events

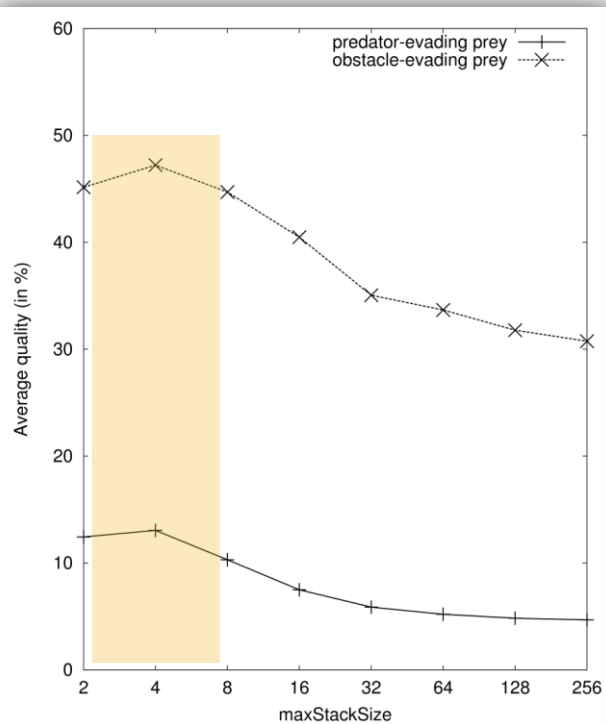
- Neutral Event
 - No positive or negative event for a number of steps
 - Half of the action sets is discarded and receives reward
 - Idea:
 - Good actions are rewarded earlier
 - Preventing of dead ends
 - Problem:
 - Error possibility high if directly followed by an event.



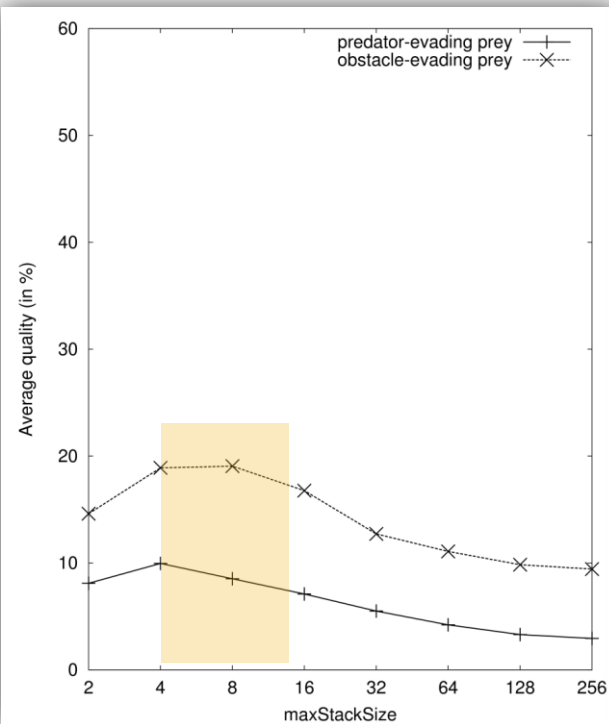
Neutral Events

- Tests have shown that a stack size of 8 is generally good for all three scenarios

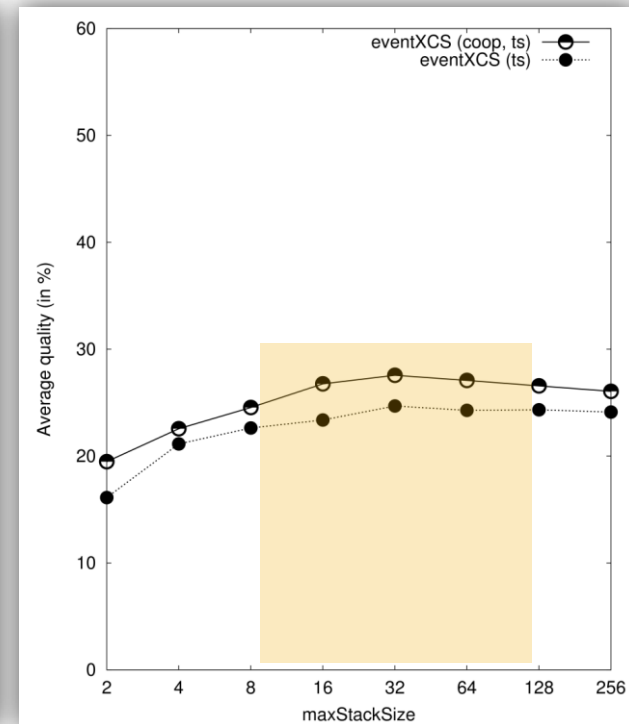
"Pillar Scenario"



"Random Scenario"

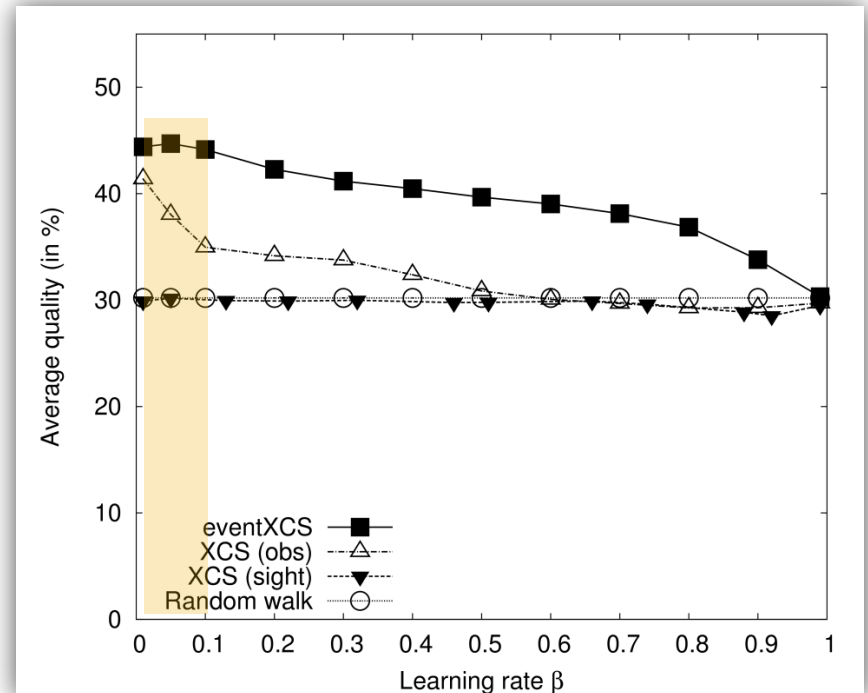


"Difficult Scenario"



Learning Rate β

- Pillar Scenario
 - Obstacle-evading prey
- Low learning rate (0.05) good, eventXCS very stable

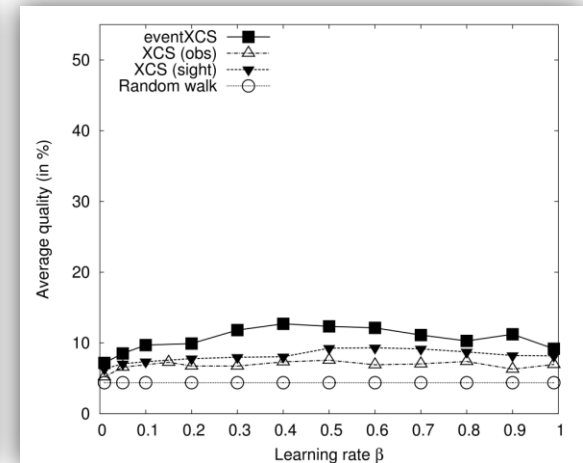
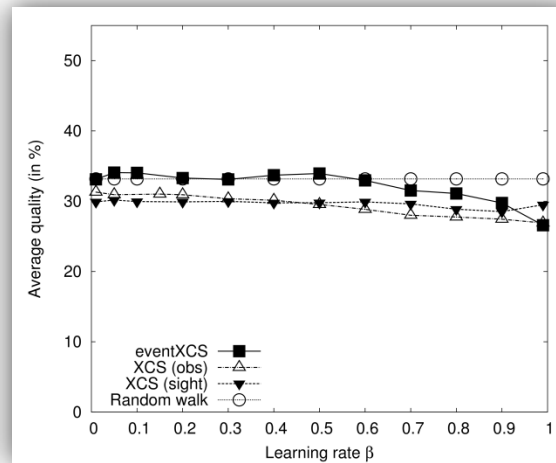
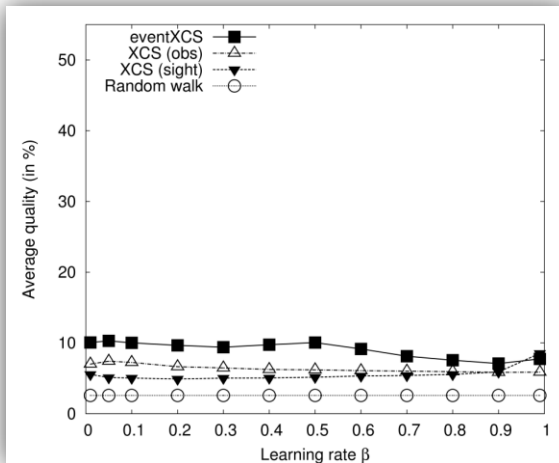


Learning Rate β

Pillar Scenario
Predator-evading
prey

Random Scenario,
Obstacle evading prey

Random Scenario,
Predator evading



Learning Rate β

- Difficult Scenario
 - Blind prey
- High learning rates show an advantage because of long distance to the prey

