



LOYOLA
UNIVERSITY MARYLAND

An Agent-Based Predator-Prey Model with Reinforcement Learning

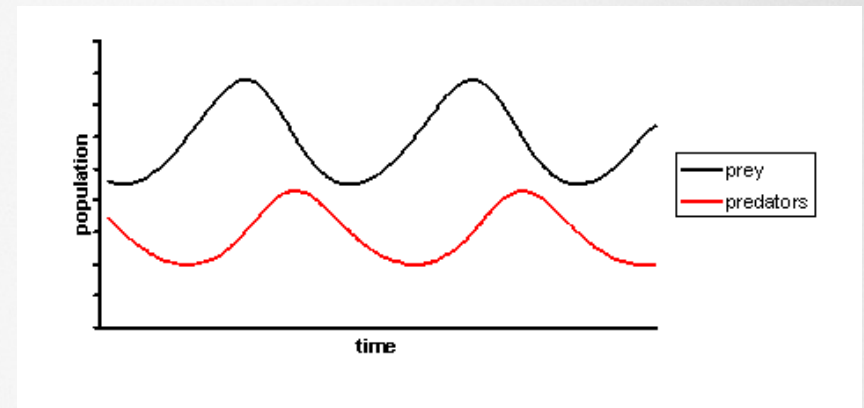
Rachel Fraczkowski, Megan Olsen
Department of Computer Science

Swarmfest 2014

Studying Predator-Prey Systems

- Impact of Environmental Scenarios
 - Invasive Species
 - Human Impact Decisions
 - Extinction
- Simulation Observations
 - Emergent behavior without cost of actual observation
 - Population Dynamics
 - Chasing Patterns
 - Homeostasis or Balance

Previous Work



- Lotka Volterra (1925)
- Cellular Automata & Biological Modeling (Ermentrout, 1993)
- Cellular Automata with Emotions (Olsen, 2010)
- Netlogo Agent-Based Model (Wilensky, 1999)
- **Goal: Agents learn biased random movement using Reinforcement Learning**



LOYOLA
UNIVERSITY MARYLAND

Introduction
Reinforcement Learning
Model
Simulation
Results
Conclusions



LOYOLA
UNIVERSITY MARYLAND

Reinforcement Learning in Psychology

- Reinforcement Learning is a method of learning which uses rewards and punishments and scheduling in order to elicit a specific behavior or action.
- B. F. Skinner's Box (1938)
- Goal of RL: To increase or decrease the probability of action occurring in the future.

Four Types of Reinforcement

| | |
|---|--|
| Positive Reinforcement : Positive stimuli given in order to increase behavior | Negative Reinforcement: Aversive stimuli added in order to increase behavior |
| Punishment: Aversive stimuli added to decrease behavior | Extinction: Behavior fades when it is no longer enforced |

Reinforcement Learning in Computer Science

- Reinforcement learning is an area of machine learning
- Software agents take actions in environment
- Maximize notion of cumulative reward
- Examples
 - Game theory
 - Simulation-based optimization
 - Control theory
 - Operations research
 - Information theory
 - Statistics
 - Genetic algorithms

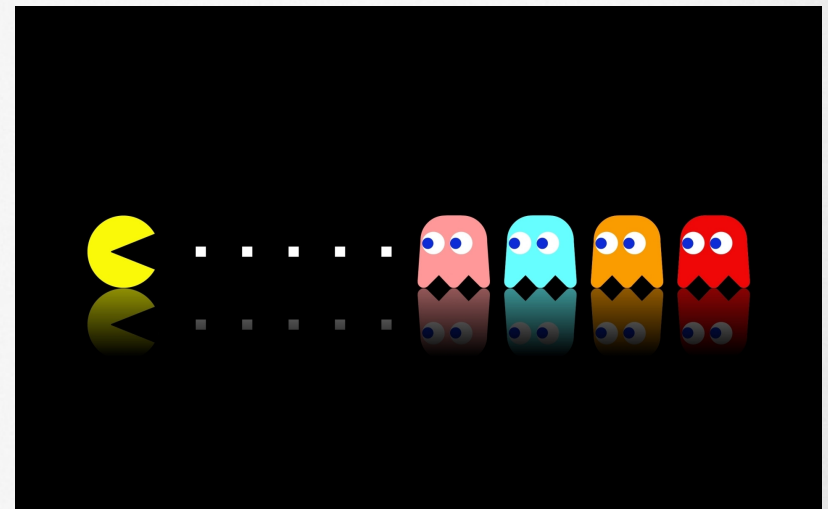


Image from technetcrew.com

Reinforcement Learning in Our Model

- Predator learns to chase prey
 - Reward movement towards prey
 - Punish movement away from prey
- Prey learns to escape predator
 - Reward movement away from predator
 - Punish movement towards predator



Image from stephsnature.com



LOYOLA
UNIVERSITY MARYLAND

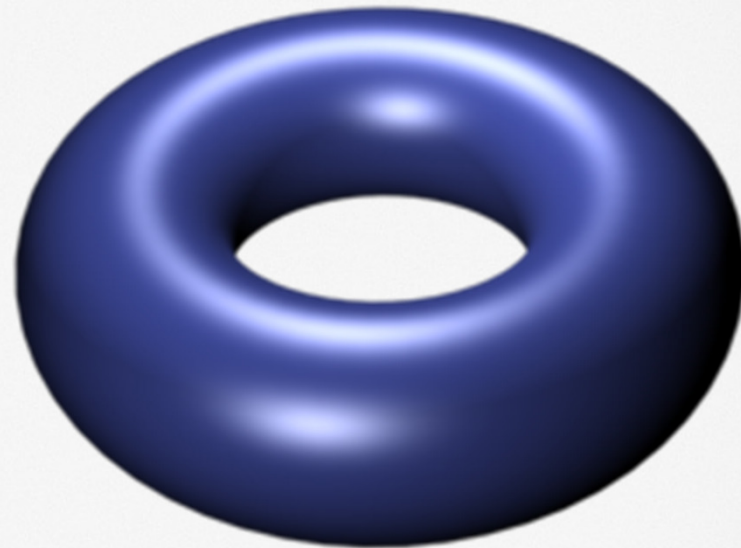
Introduction
Reinforcement Learning
Model
Simulation
Results
Conclusions



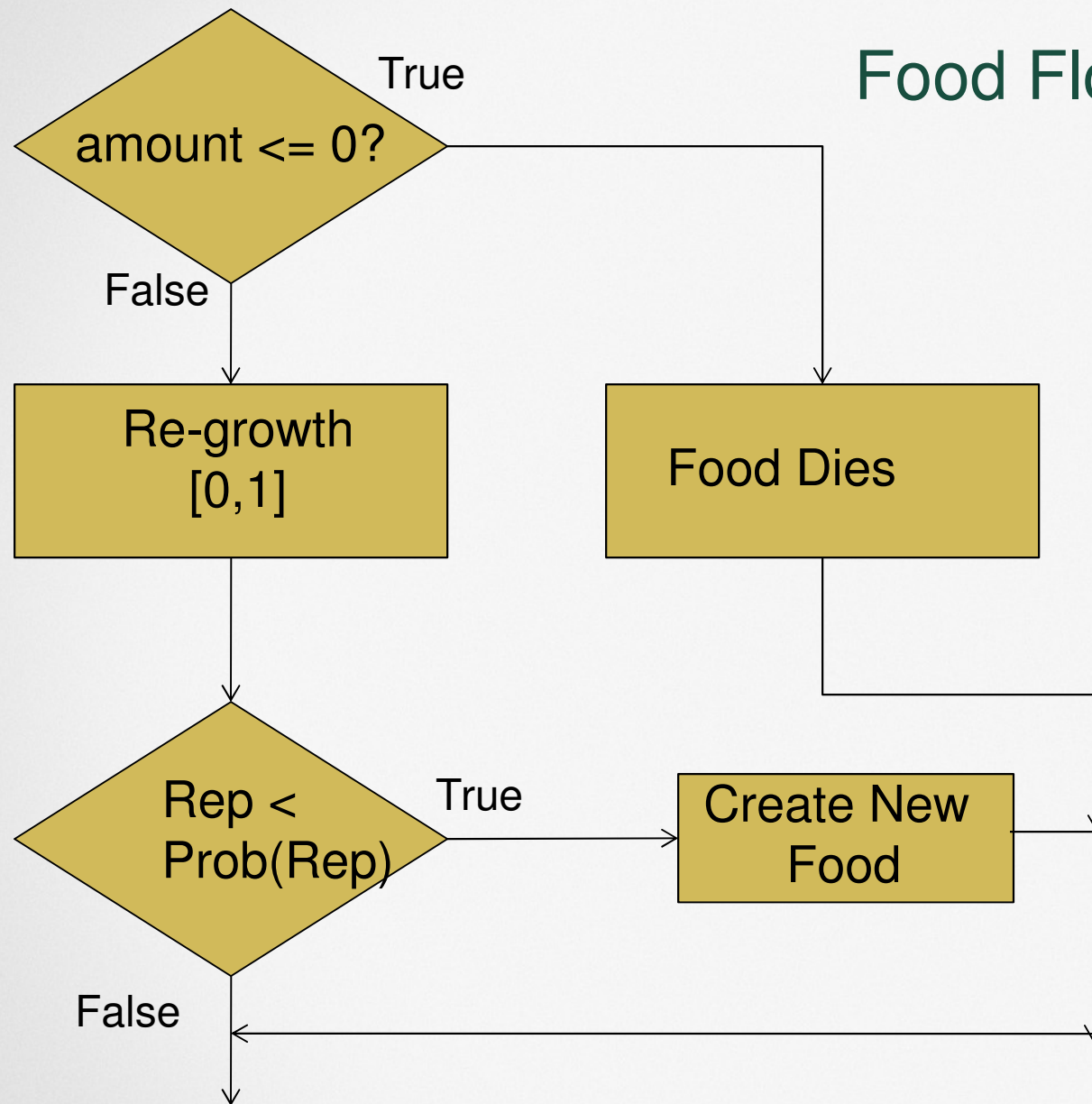
LOYOLA
UNIVERSITY MARYLAND

Our Model

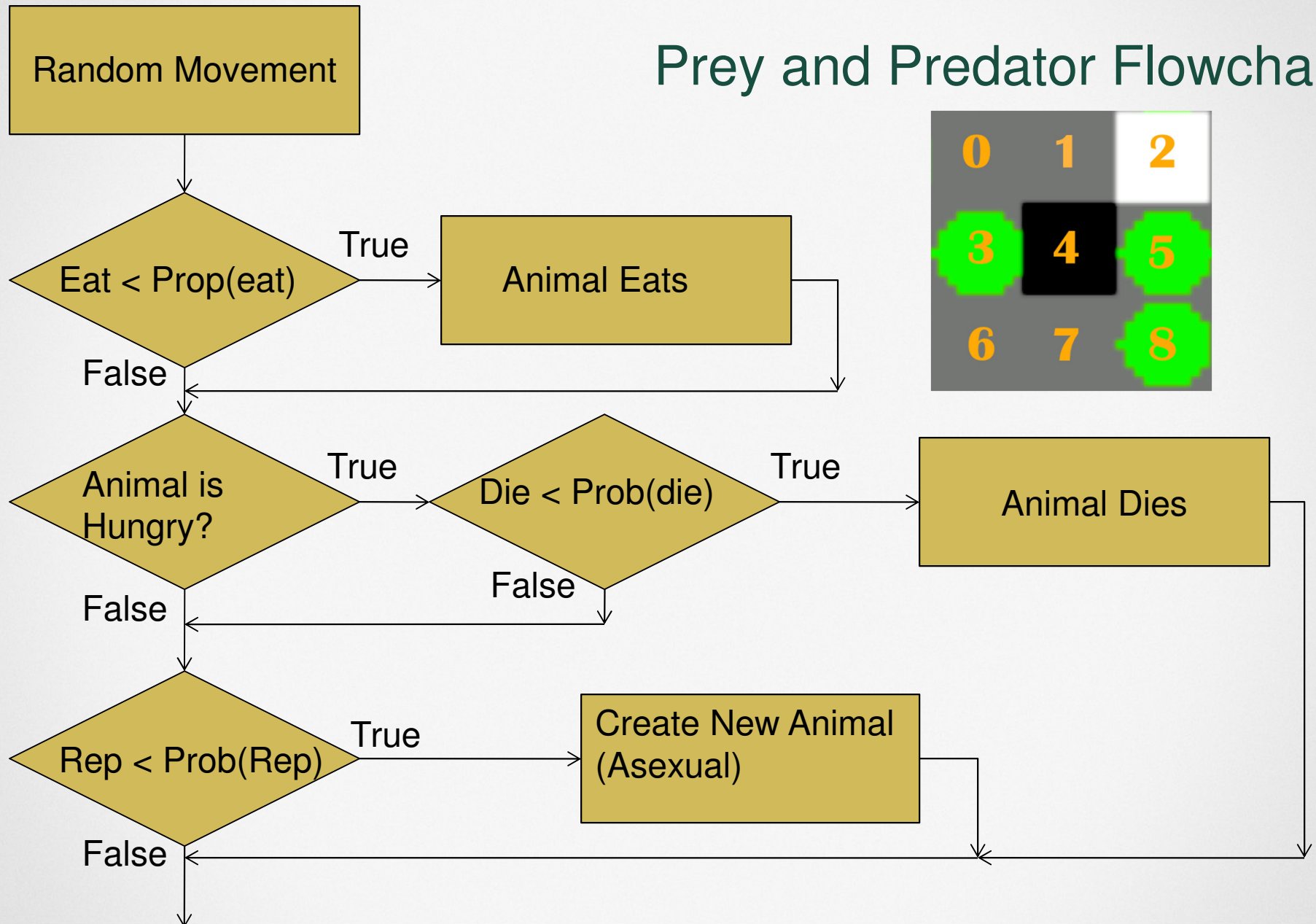
- MASON Framework
- 2D Grid
 - Torus
- Agents
 - Food
 - Predator
 - Prey



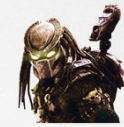
Food Flowchart - Timestep



Prey and Predator Flowchart



Agents Learn Movement Probabilities



Predator



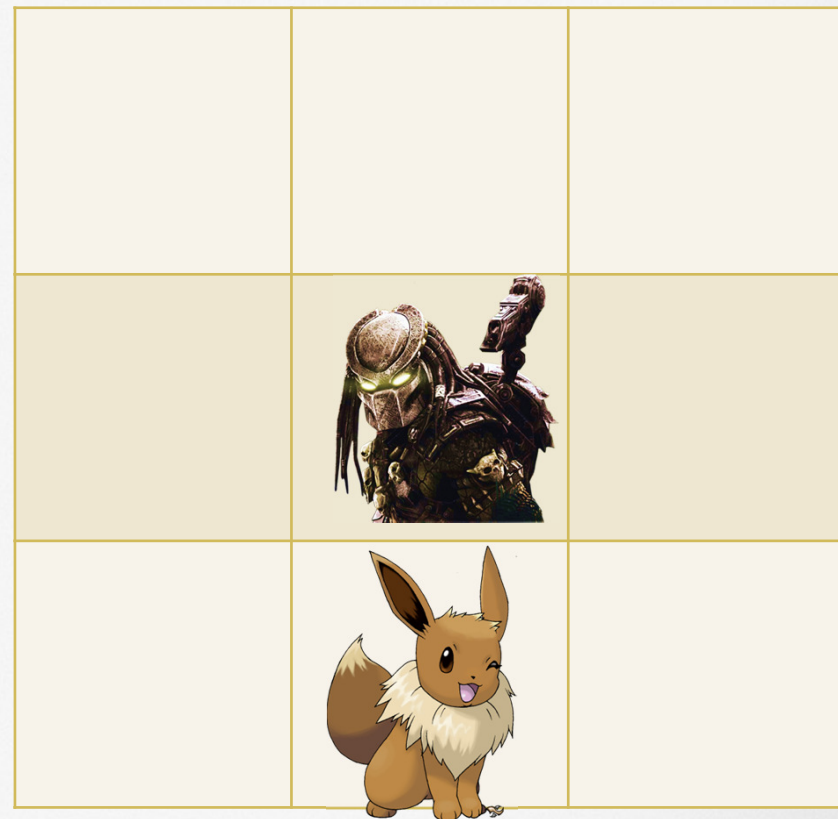
Prey

Movement Array

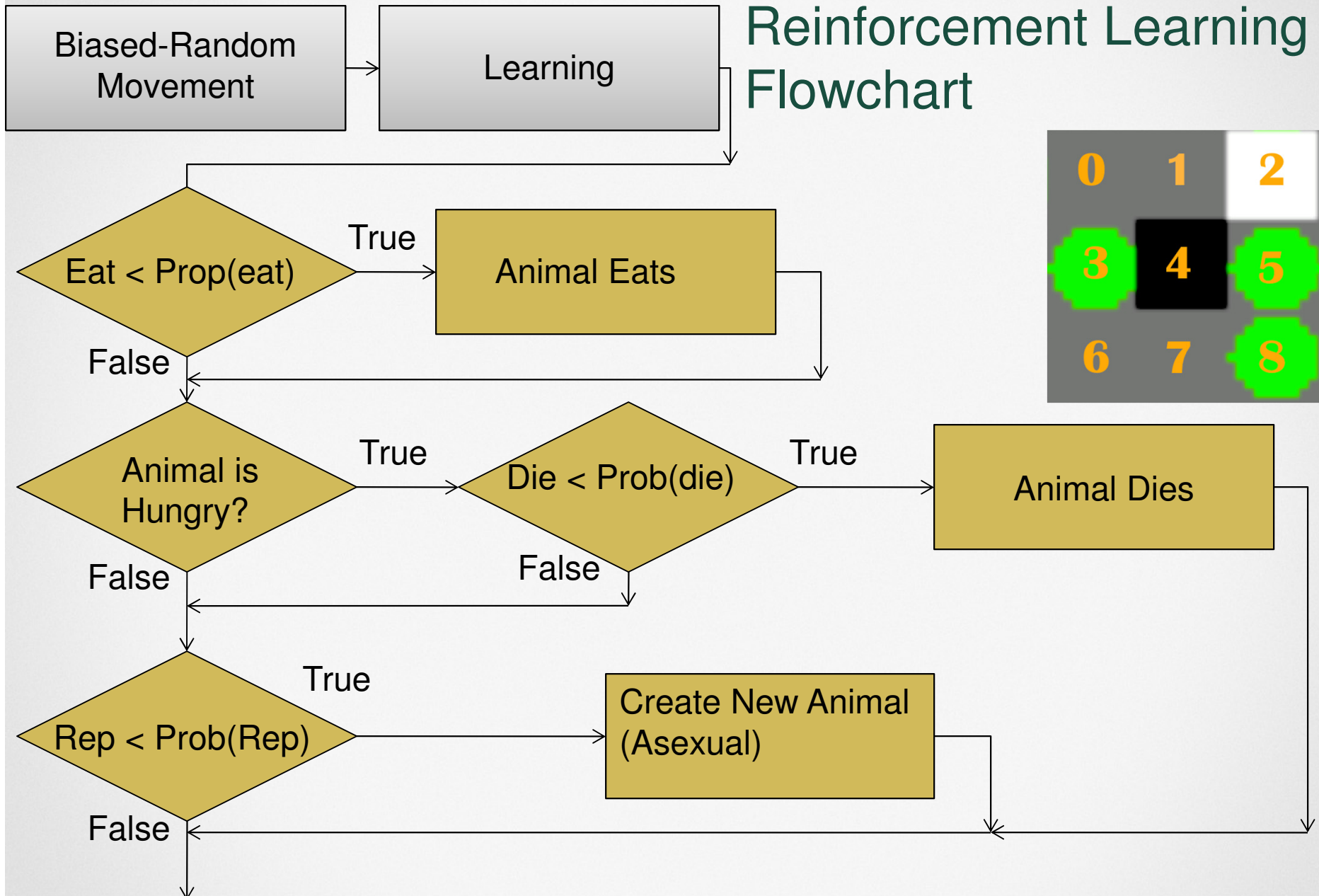
{ 11.11, 11.11, 11.11,
11.11, 11.11, 11.11,
11.11, **11.11**, 11.11 }

Learned Array

{ 6.235, ***1.235***, .235,
6.235, 6.235, .235,
6.235, ***67.11***, 6.235 }



Reinforcement Learning Flowchart





LOYOLA
UNIVERSITY MARYLAND

Introduction
Reinforcement Learning
Model
Simulation
Results
Conclusions



LOYOLA
UNIVERSITY MARYLAND

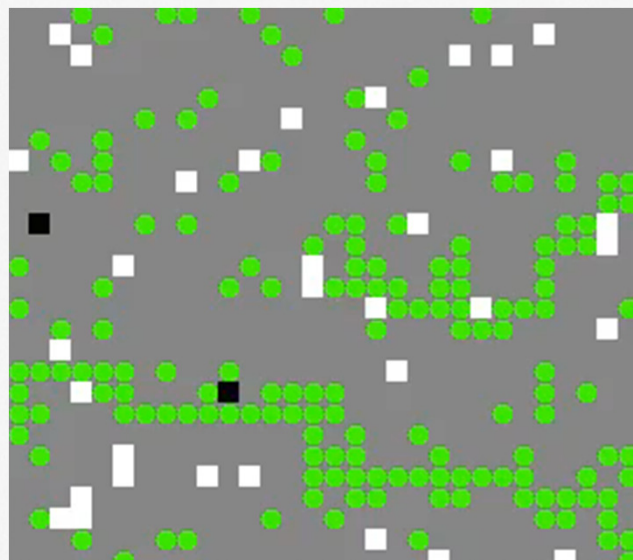
Simulation Sample

World

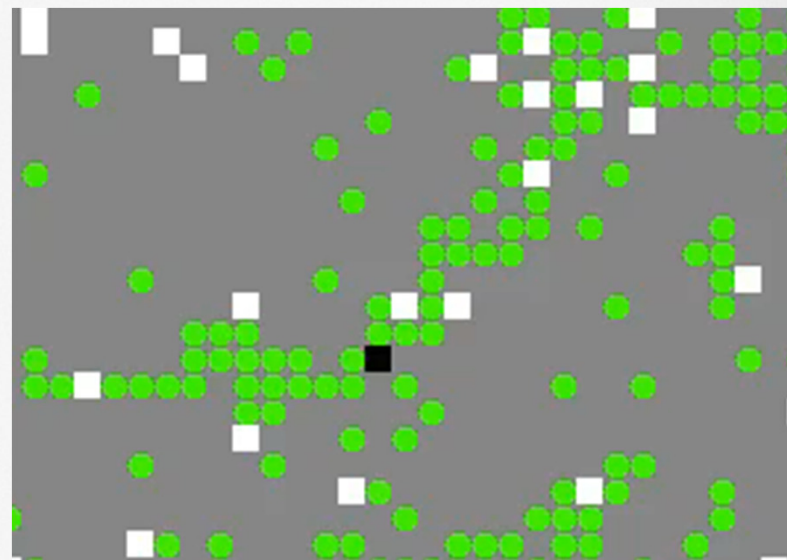
Predator

Prey

Food



No Learning



Learning (Prey)

Analyzing the System

- Goal: Have agents learn to move in biased manner from their environment and experience
- Hypotheses:
 - The species learning will have an advantage in the system
 - With co-learning, agents will learn from one another
- Phases:
 - No Learning
 - Predator Learning Only
 - Prey Learning Only
 - Predator and Prey Learning

Simulation

15 replications for each set of parameters

Prey > Predator (population and reproduction)

Reproduction rate > death rate

| Parameters | Predator | Prey |
|--------------------------------------|--------------|--------------|
| Population | 25-100 | 200-800 |
| Reproduction Rate | 5%-20% | 10%-20% |
| Initial Death Rate | .1%-10% | .1%-1% |
| Hunger Minimum / Reproduction Age | 15 timesteps | 12 timesteps |
| Hunger Death Mod | 1x-1.5x | 1x-1.5x |



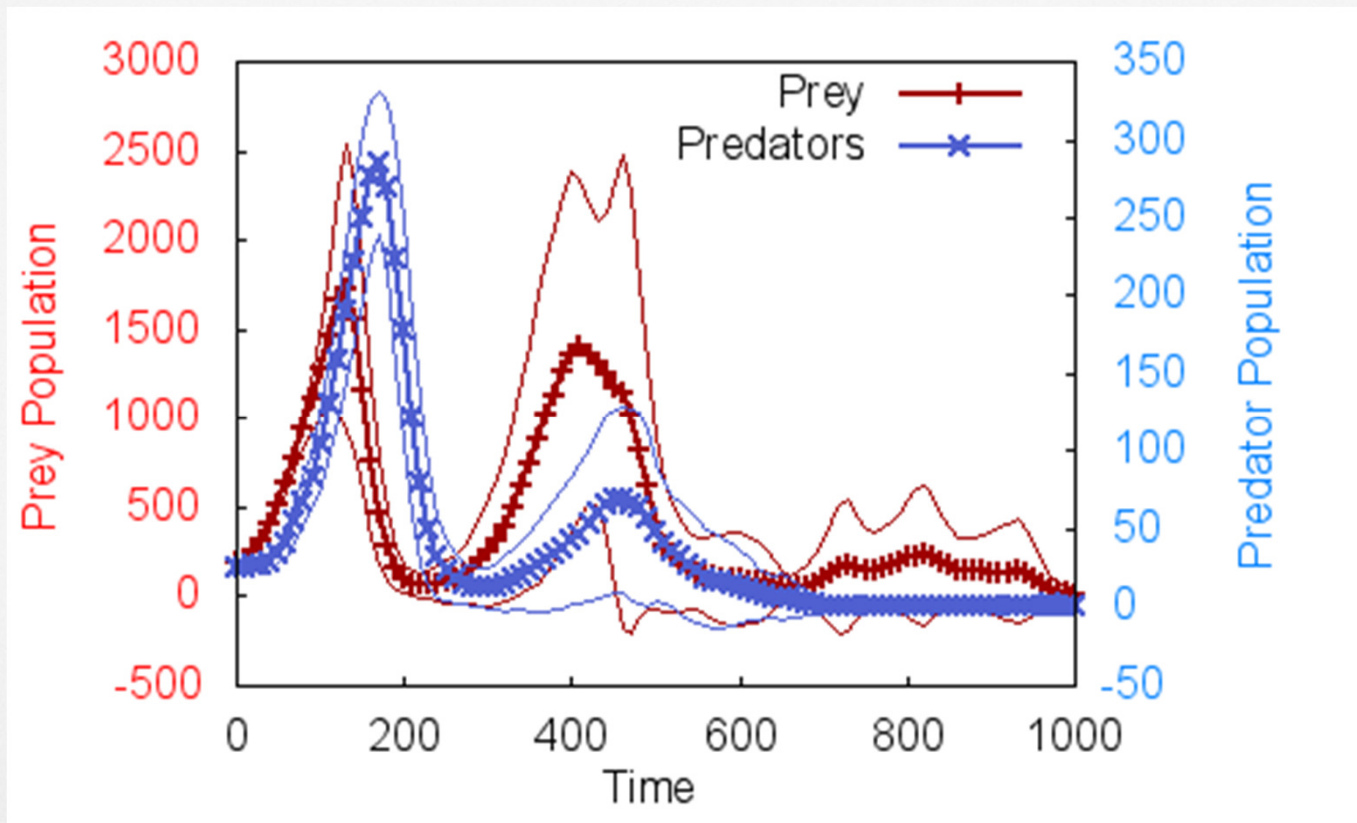
LOYOLA
UNIVERSITY MARYLAND

Introduction
Reinforcement Learning
Model
Simulation
Results
Conclusions



LOYOLA
UNIVERSITY MARYLAND

Preliminary Results



Preliminary Results

- Prey learning shows improvement
- Predator and Prey Learning to stay more often
- Both Learning shows improvement from Predator learning

| | outran | caught | prey Stay | pred Stay | ending | prey Count | pred Count | prey Eat | prey Hunger | pred Hunger |
|------------|------------|------------|------------|------------|------------|------------|------------|------------|-------------|-------------|
| prey learn | 76% | 60% | 80% | 60% | 60% | 72% | 56% | 56% | 68% | 64% |
| pred learn | 20% | 24% | 20% | 72% | 4% | 12% | 12% | 20% | 12% | 4% |
| both learn | 28% | 32% | 52% | 72% | 4% | 16% | 20% | 32% | 12% | 0% |

Learning Has an Impact

- Predator and Prey experience improved behavior (eating)
- Prey system has expected outcomes
- Predator system has unexpected outcomes
- Both learning shows an average of other two systems



LOYOLA
UNIVERSITY MARYLAND

Introduction
Reinforcement Learning
Model
Simulation
Results
Conclusions



LOYOLA
UNIVERSITY MARYLAND

Conclusions

- Agent-Based Model with reinforcement learning agents
- Observed expected population fluctuations
- Prey learning and Both learning show improvements to system
- Predator & prey learning to stay

Future Work

- More parameter testing and results
- Changes in learning algorithm
- Agents could learn more complex cognitive functions
 - Memory
 - Emotional Experience

