



ELTE | IK  
INFORMATIKAI KAR

# Multi-Agent Simulation & Learning

## Introduction to Machine Learning

Computer Science BSc Course, ELTE Faculty of Informatics

László Gulyás

Associate Professor  
Department of Artificial Intelligence  
[lgulyas@inf.elte.hu](mailto:lgulyas@inf.elte.hu)



ELTE | IK

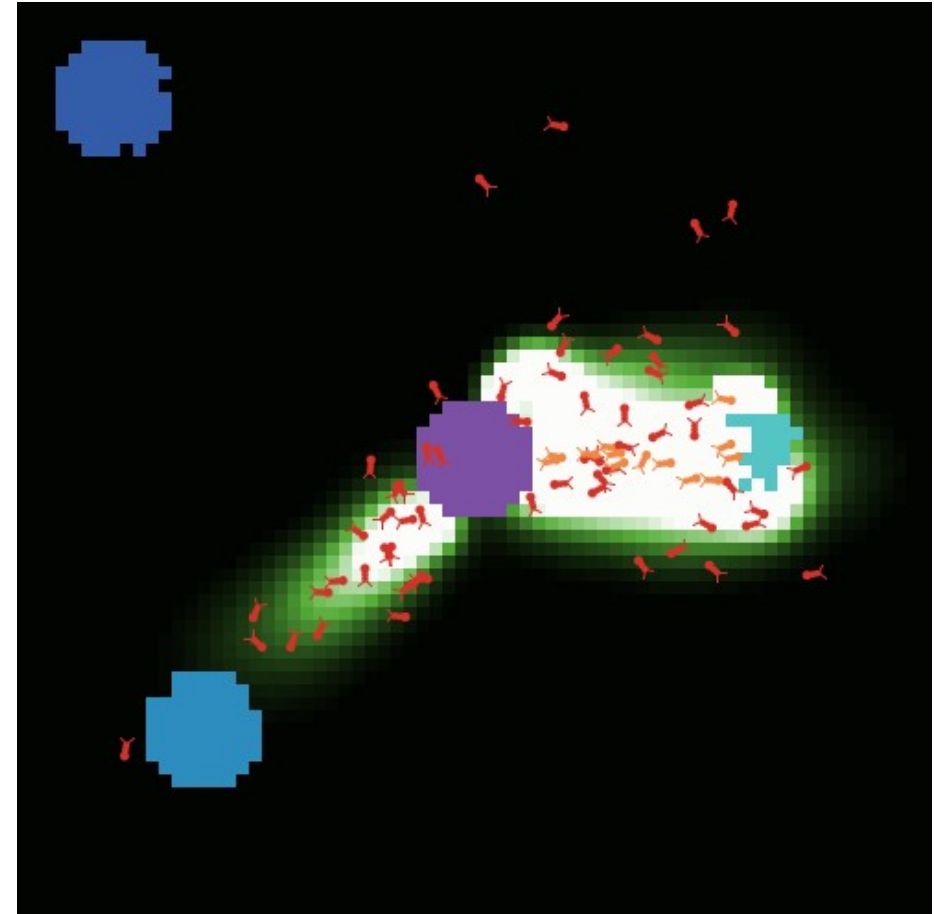
DEPARTMENT OF  
ARTIFICIAL  
INTELLIGENCE

# Motivation

## Multi-Agent Systems

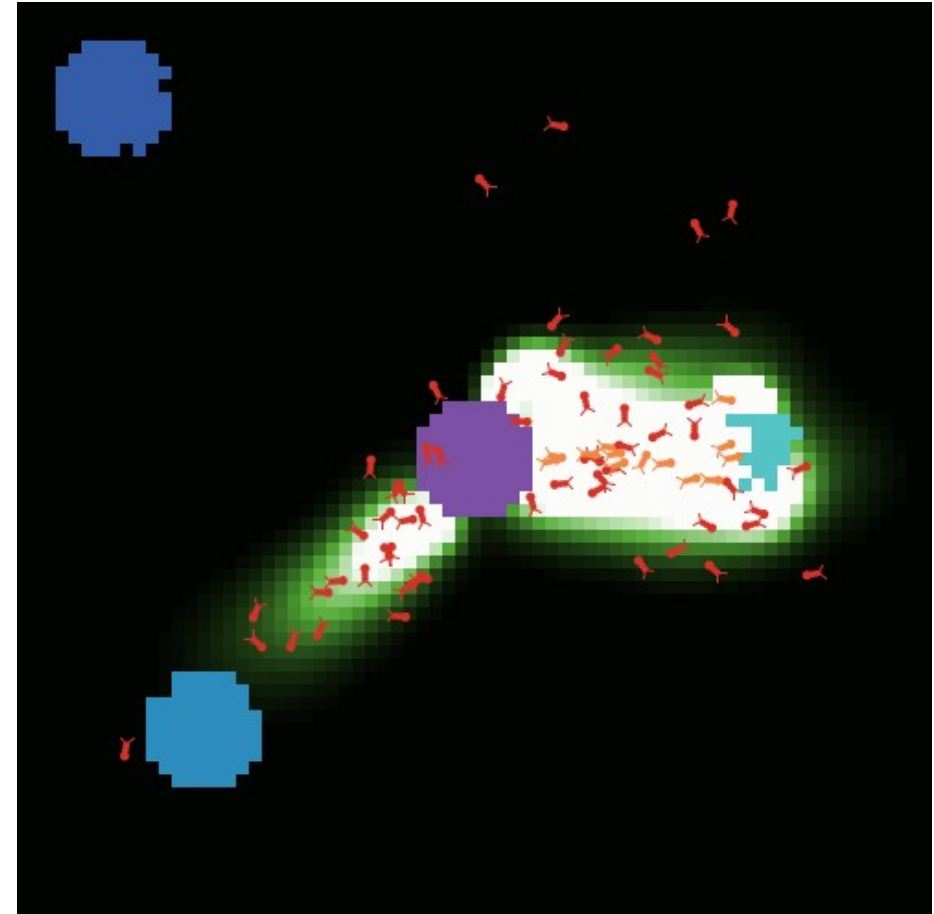
# Who is Intelligent?

- Foraging Ants



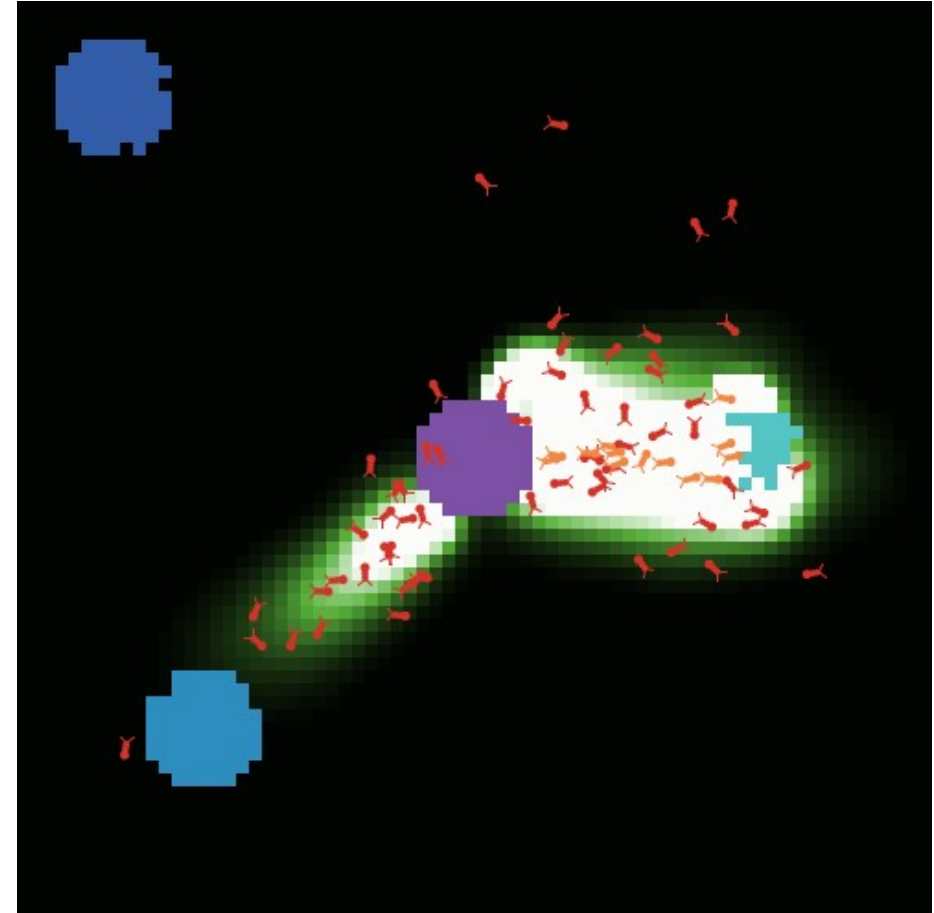
# Who is Intelligent?

- Foraging Ants
  - Intelligent?
  - Solves the problem
  - Robust and cheap...



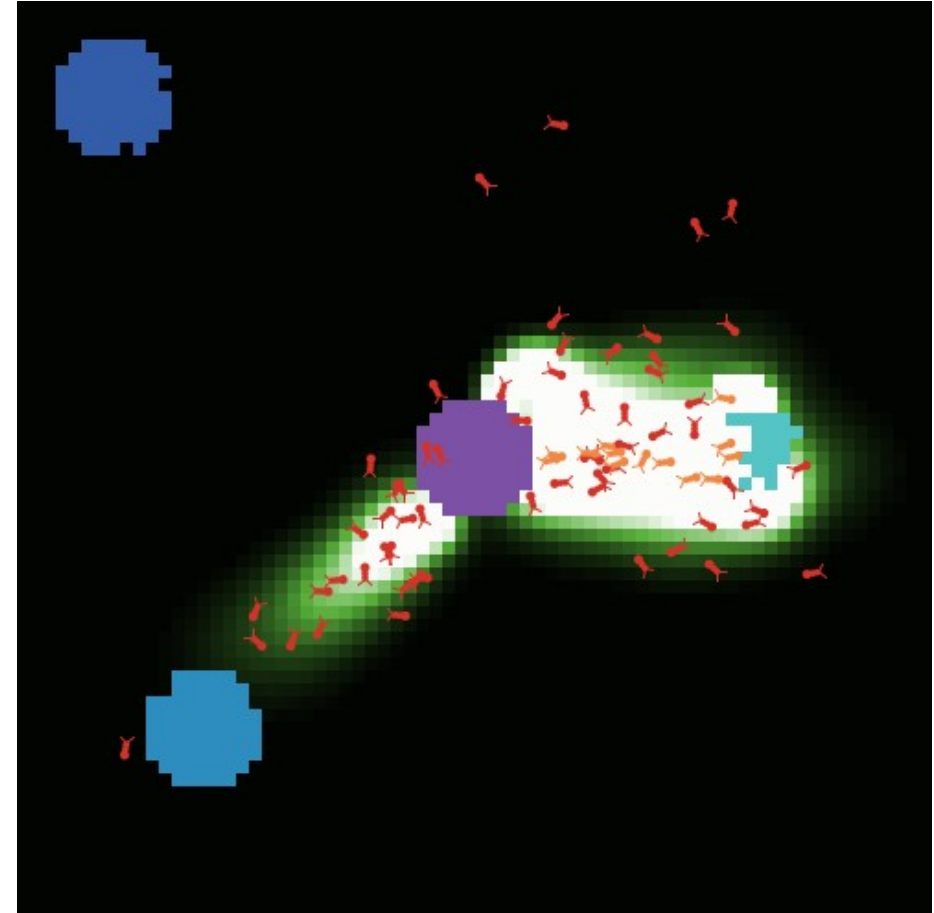
# Who is Intelligent?

- Foraging Ants
  - Intelligent?
  - Solves the problem
  - Robust and cheap...
- In the eye of the beholder



# Who is Intelligent?

- Foraging Ants
  - Intelligent?
  - Solves the problem
  - Robust and cheap...
- In the eye of the ~~beholder~~ observer
  - And there are different levels of observation (consideration)



# Micro and Macro Behavior

---

- Building Systems
  - From top-down
  - From bottom-up
- When parts also have autonomy
  - Make decisions (have behavior)
  - Are potentially rational/intelligent
  - Come from different (perhaps unknown) provenance
  - Have potentially different goals
- When intelligence is (also) measured at system level
  - Collective Intelligence

# Unintended consequences

## Driving on the road

---

© CGP Grey <https://www.cgpgrey.com/>





# The micro-macro dichotomy

How to work with it?

# Basic Notion





# Emergence

- Something observable at a ,higher level'
  - That does not exist at ,lower levels'
  - That is not expressable at ,lower levels'
- This can be a property or a behavior
- Hard concept to define formally
  - Subject to discussions and interpretations
- **Yet, at the core of ,Micro vs Macro'**

# Two Related Topics

---

## **Analysis: Agent-Based Simulation**

Experimenting with

- Possible *micro* rules that
- *Generate*
- (observed) *macro* behavior

→ A tool of explanation

## **Construction: Multi-Agent (Reinf.) Learning**

- Learning to Cooperate
- Learning to Swarm

# Agent-Based Simulation

An Example, A Tool

# New Segregation: Races accept divide



[US News Excerpt]

**Exclusive Report**

## **New segregation: Races accept divide**

**But experts say financial, social costs of living apart are just as detrimental**

**By Ron French / *The Detroit News***

More than four decades after Americans fought and died to end segregation, many in Metro Detroit are comfortable living apart.

# Why?

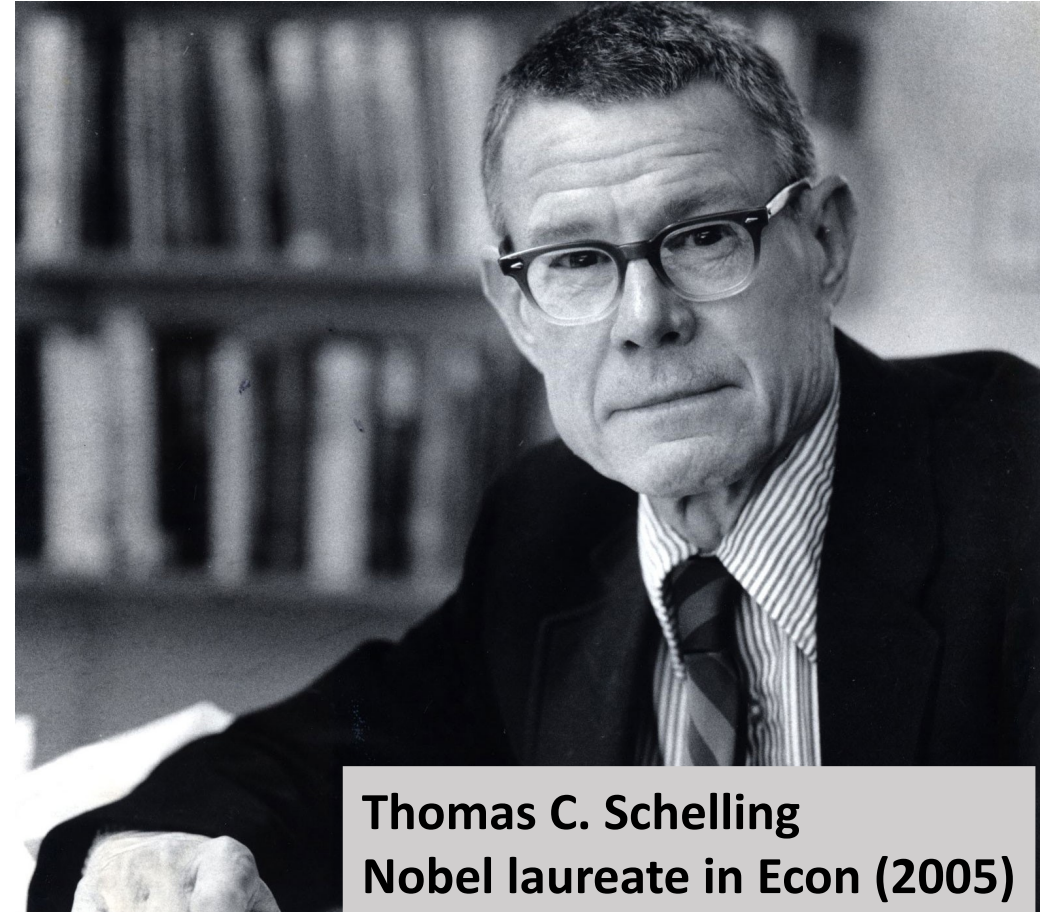
---

- Endless number of opinions
  - Economical reasons
  - The level of racism in the society
  - Etc.
- Untested opinions
  - To test: *simplifications* → *models*



# A Model of Housing Segregation by *Thomas C. Schelling* (1978)

- Residential choices
  - Stylized 2D environment
  - “Oranges” and “Blues”
  - The level of personal tolerance (given as a %)
- **Where does a general 60% tolerance level lead us?**
  - **And 70%?**



Thomas C. Schelling  
Nobel laureate in Econ (2005)

# A Model of Housing Segregation by *Thomas C. Schelling* (1978)

**Tolerance** (int) in [0,100]: (%)

**Neighbors** (int) in [0,100]:  
#neighbors\_of\_other\_color //  
#all\_neighbors

**Happy** (boolean):

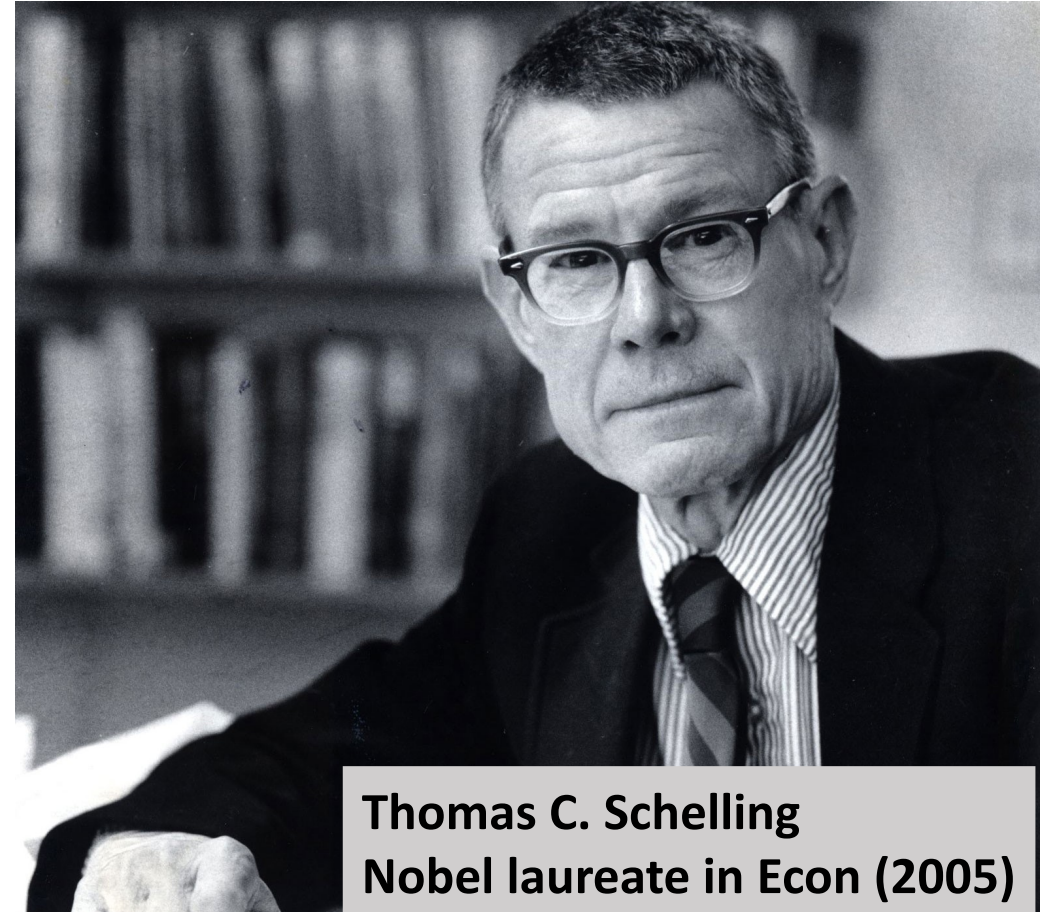
Neighbors <= Tolerance

**Movement Rule:**

If (not Happy):  
Move\_to\_an\_empty\_location

**Variants:**

- Move\_to\_random\_empty\_location\_if\_happy\_there
- Move\_to\_closest\_empty\_location
- Etc.
- Various neighborhood definitions possible



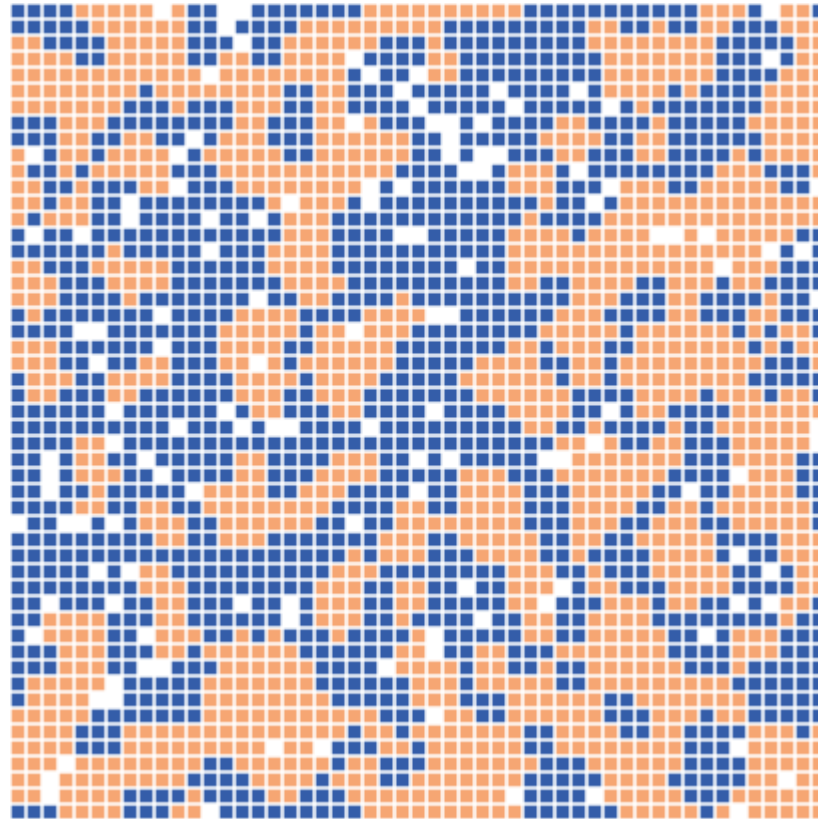
**Thomas C. Schelling**  
**Nobel laureate in Econ (2005)**

# 70 percent tolerance, random initialisation

---

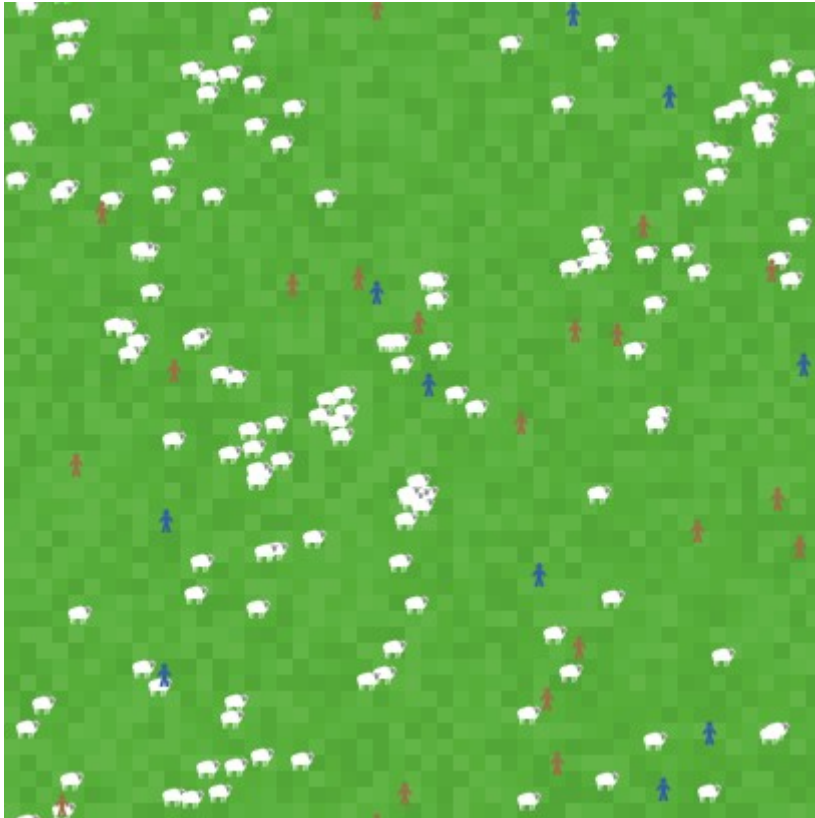
# 70 percent tolerance, random initialisation

---

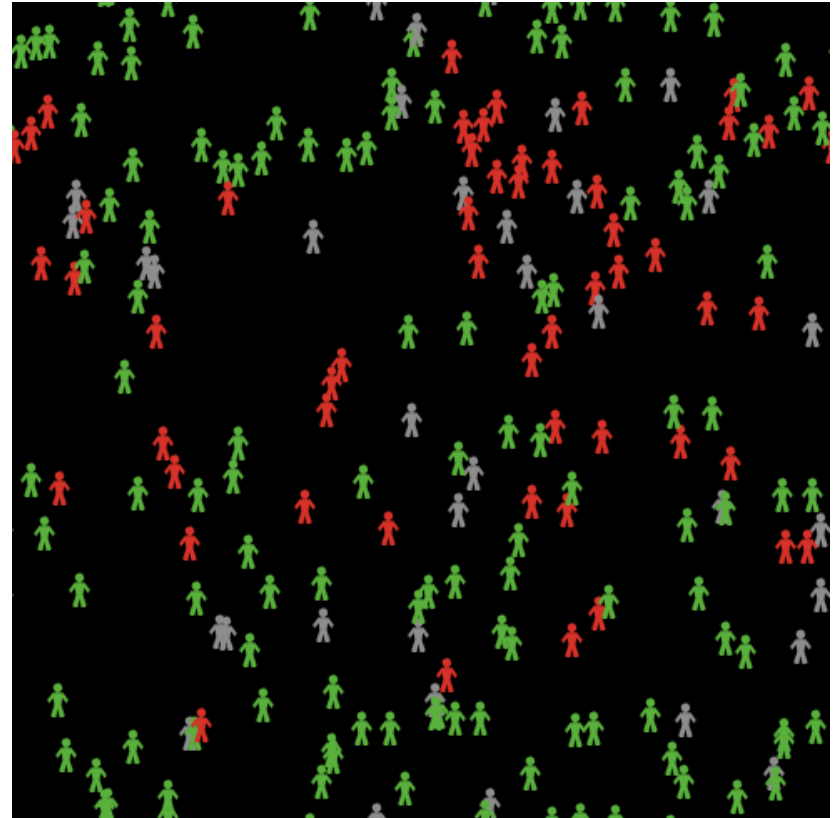


# NetLogo

<https://ccl.northwestern.edu/netlogo/>



Models library/Biology/Shepherds



Models library/Biology/Virus

# Multi-Agent (Reinf.) Learning

Some Examples

# Goal – „Learning to Swarm”

---

- Training teams of mobile robots
  - To solve a problem collectively
  - → Multi-Agent Reinforcement Learning (MARL)
- „Swarm robotics in spirit’:
  - No control hierarchy
  - No explicit, direct communication
  - No complex negotiation protocols
  - No explicit dependence on team size
    - Cf. Graceful degradation



# Background of Examples

---

## Technical Setup

- StableBaseline3
  - Multi layer perceptron (MLP)
  - LSTM
- Training
  - Proximal Policy Optimisation
  - Q-learning
  - Actor-Critic Model
- Negative reward for collision

## Challenges Explored

- Traditional models
  - Fixed input size (observation space )
- Varying #agents
  - Challenge →
  - Masking, based on distance
  - Pooling based on distance (k-Nearest Neighbors)



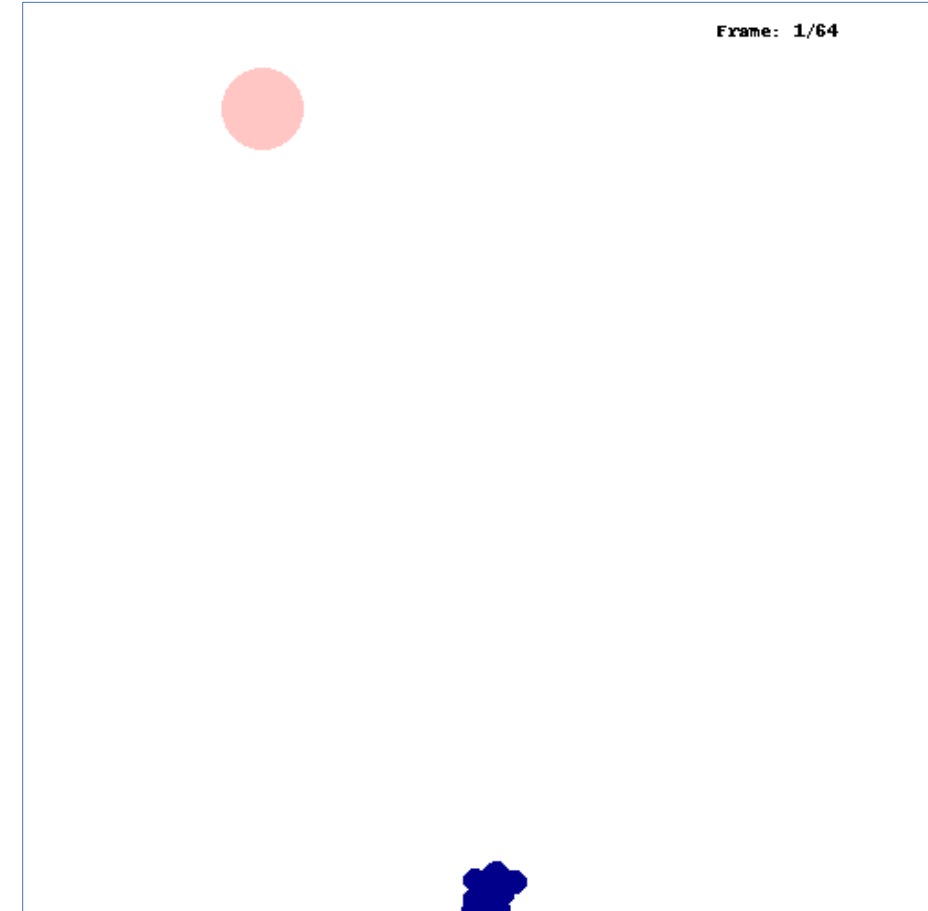
# Simple Tag Game with Multi-Agent Actor Critic policy learning

- Normal approach
  - Single agent policy learning for each agent
- The Multi-Agent Actor Critic
  - Decentralized actors (policies)
  - Centralized critic
  - → Info sharing
- Better for multi-agent environments



# Move the team to the target area

- Conditions
  - Agents have limited vision
    - N closest agent and the goal state if in vision range
  - No direct communication
  - Grid environment
  - Terminate: >80% at target
- Approach
  - MLP model and PPO policy learning
- Behavior:
  - Agents spreading out as much as they can see each other
  - After finding the goal, they oscillate to propagate the information

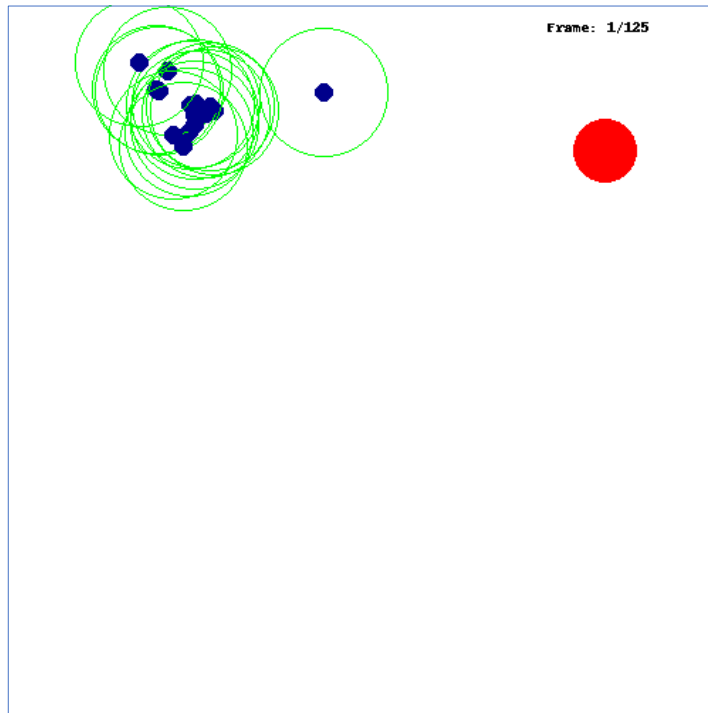


# Move the team to the target area

## 2 distinct strategies

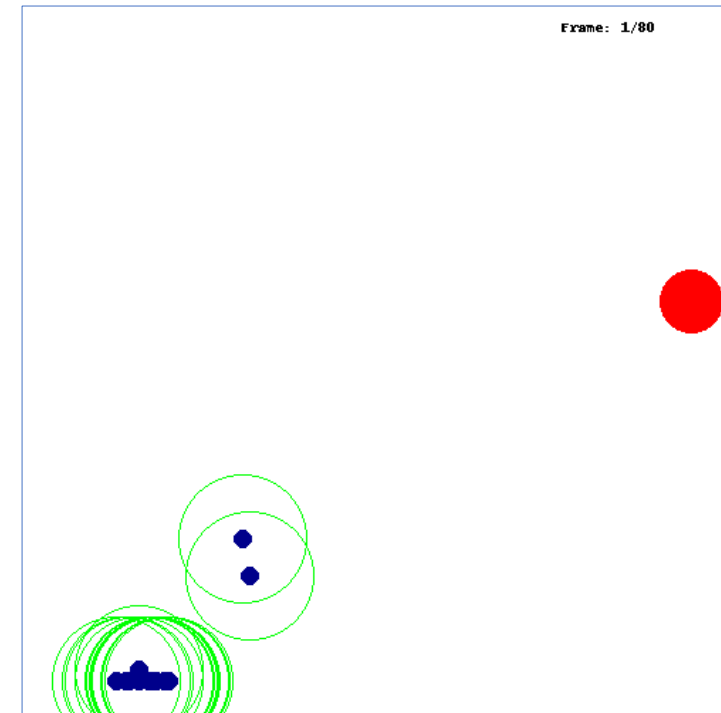
### Fast Exploration

Spread wide, communicate later



### Fast communication

Stick and explore together



# Move to the Target

## Multi-Agent Multi-Target Case

---

- Incremental and curriculum learning
  - Agents learn step by step from individual “walk” to move collectively

Punishment for colliding with  
obstacles

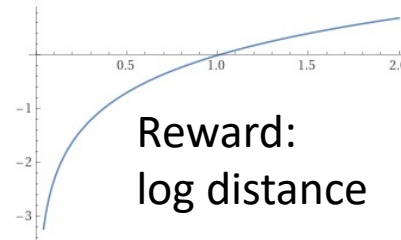
**Red:** target, **Blue:** agent, **Black:** obstacle

# Move to the Target

## Multi-Agent Multi-Target Case w/o incremental learning

**Red:** target, **Blue:** agent, **Black:** obstacle

- Non-linear (log) reward



- Maintains local focus
- Helps avoiding collision

Before

After

- Simplified observation space
  - K nearest objects
  - Same trained model for arbitrary #agents, #targets

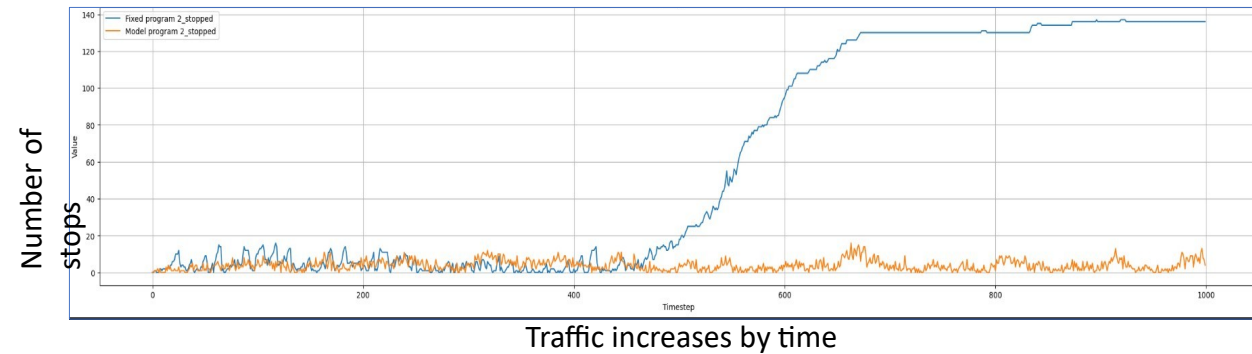
# Traffic Signal Control with local communication

## Classic approach

- Independent intersections, or
- Centralized control

## Our approach

- Independent intersections (agents)
  - Communicating with nearest neighbors
- Agent classes
  - Based on #neighbors





ELTE | IK  
INFORMATIKAI KAR

# Thank you!

László Gulyás

Associate Professor  
Department of Artificial Intelligence

[lgulyas@inf.elte.hu](mailto:lgulyas@inf.elte.hu)



ELTE | IK

DEPARTMENT OF  
ARTIFICIAL  
INTELLIGENCE