



# Artificial Intelligence

## Reinforcement Learning Agent for the Snake Game

### Our Team

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### Course

Artificial Intelligence

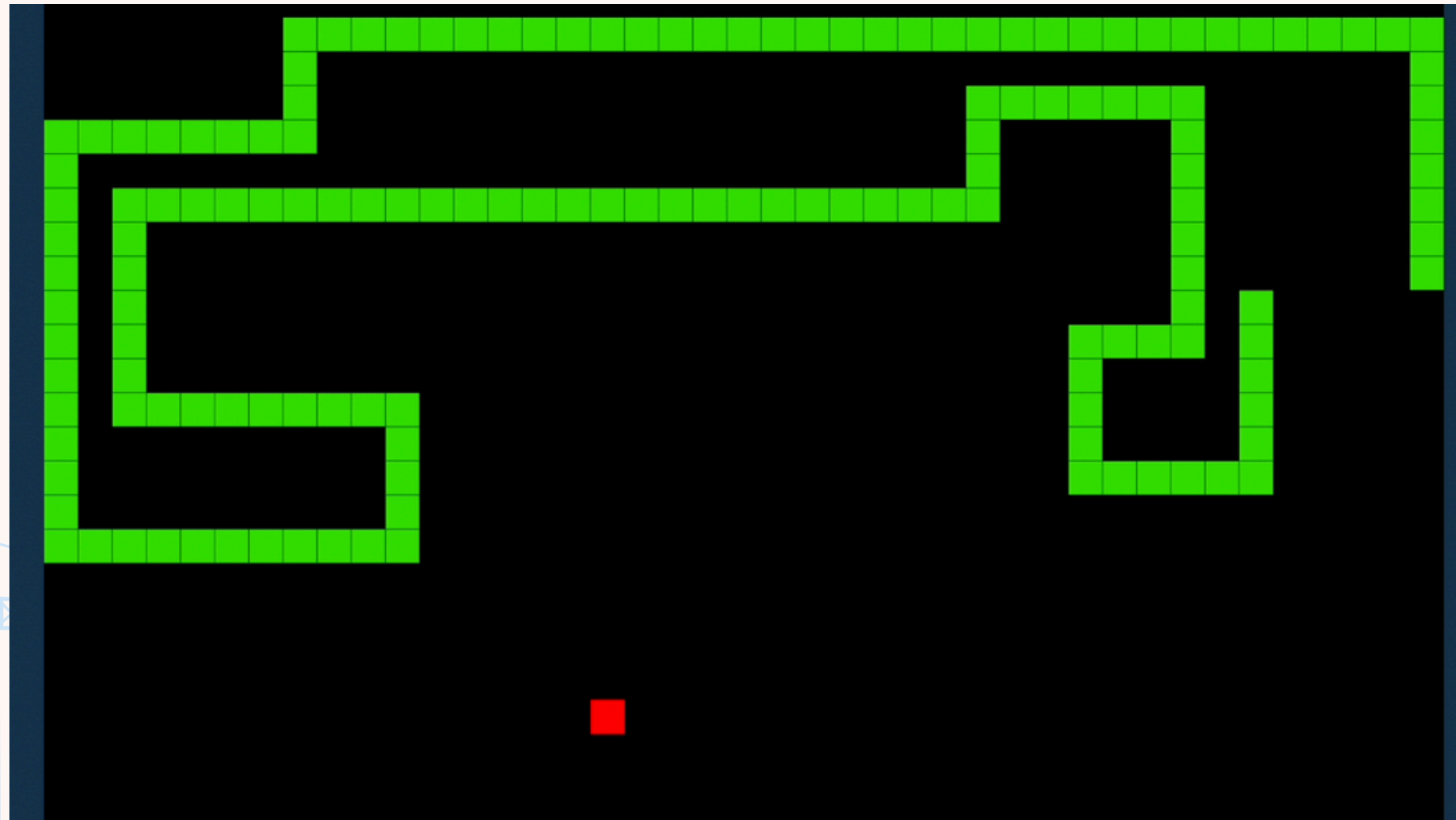
### Instructor

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# Project Overview

- Built a custom 10×10 Snake game environment.
- Implemented Q-learning agent from scratch.
- Created baseline random policy for comparison.
- Added a graphical Pygame game with Human & AI modes.
- Integrated sound effects (eat + game over).
- Goal: understand RL behavior and visualize learned strategy.



# Environment & Rewards

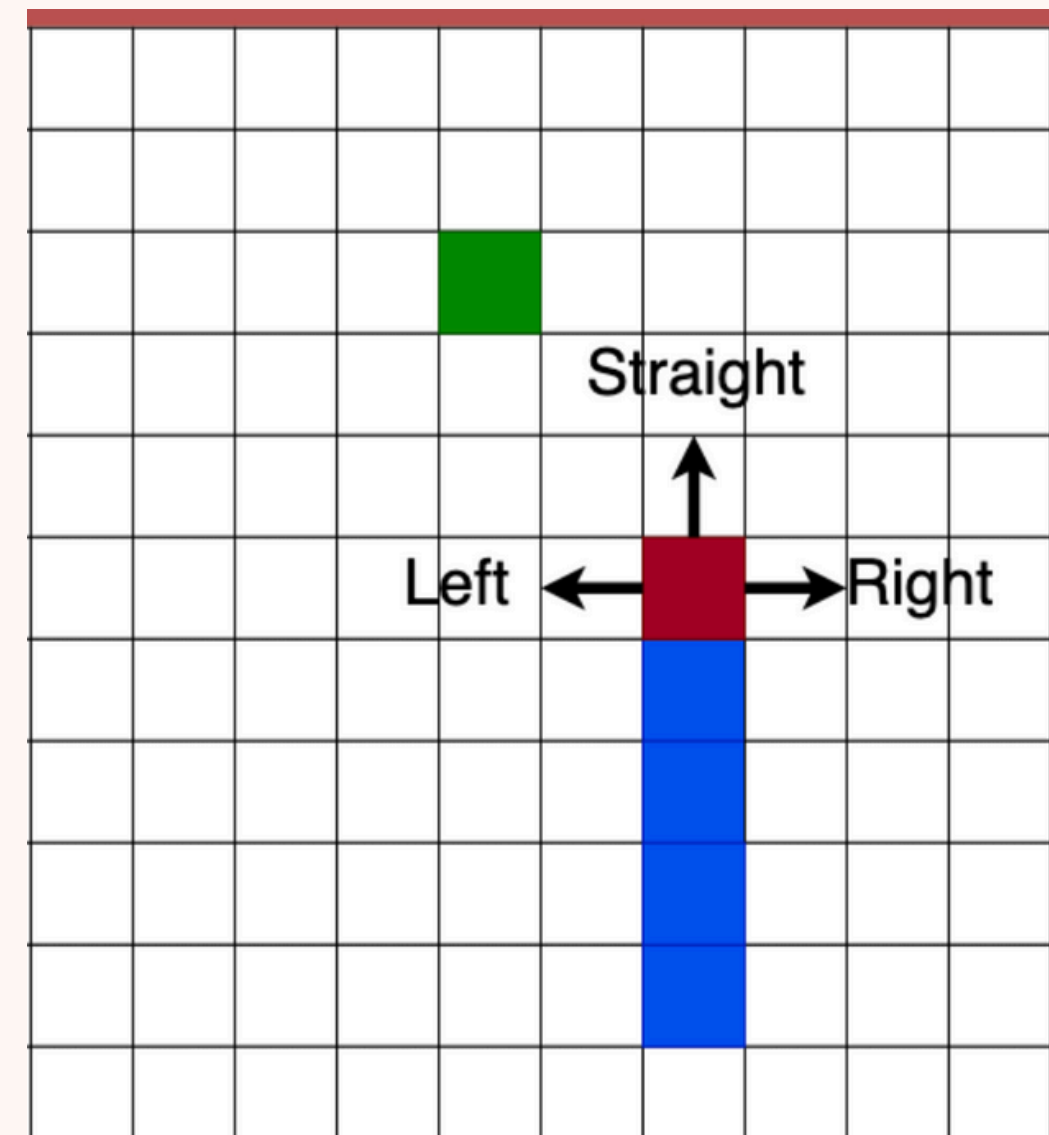
## State Representation:

(snake\_x, snake\_y, food\_x, food\_y)

Actions: Up, Down, Left, Right

## Reward Function:

- +1 → eat food
- -1 → hit wall
- +0.1 → move closer to food
- -0.1 → move farther from food
- 0 → normal move
- Episode ends on wall collision





# Q-Learning Method

## Update Rule:

$$Q(s,a) = Q(s,a) + \alpha (\text{reward} + \gamma \max_{a'} Q(s')) - Q(s,a)$$

## Hyperparameters:

- Learning rate  $\alpha = 0.1$
- Discount  $\gamma = 0.9$
- Exploration  $\epsilon = 0.1$
- Episodes = 2000

## Q-table stored using:

- `defaultdict(float)`



# Results: Random Baseline vs RL Agent

## Random Baseline (200 episodes)

- Reward:  $-0.83$
- Foods eaten: 0.17
- Survival: 30 steps

## Q-learning Agent (last ~100 episodes)

- Reward:  $+0.82$
- Foods eaten: 1.27
- Survival: 12 steps
- Trained using 5000 episodes (Q-table generated)
- Final Q-table size ~ thousands of learned state-action pairs

## Interpretation:

RL agent successfully moves toward food instead of wandering.  
Baseline behaves randomly and almost never finds food.





# Pygame Visual Game

## Features Added

- Human control (WASD / Arrow keys)
- AI-controlled gameplay using saved Q-table
- Wall-collision logic
- Smooth grid rendering
- Sound effects:
  - eat\_drink.wav
  - game\_over.wav

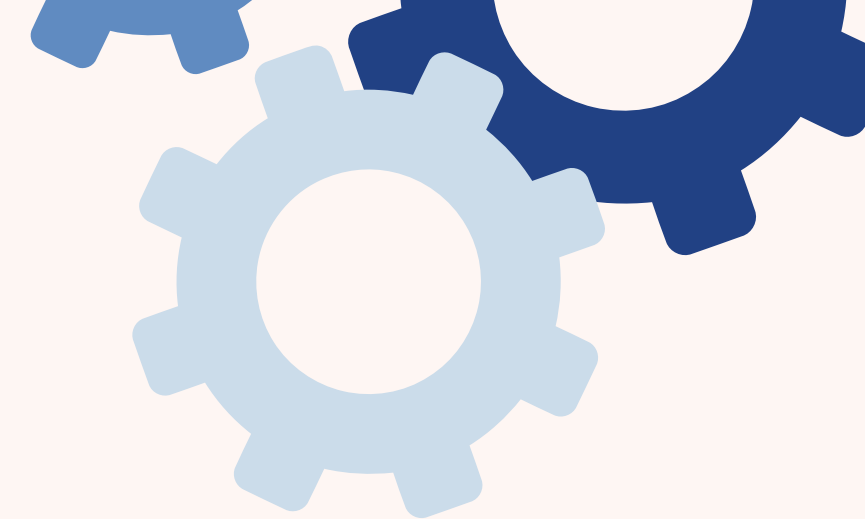
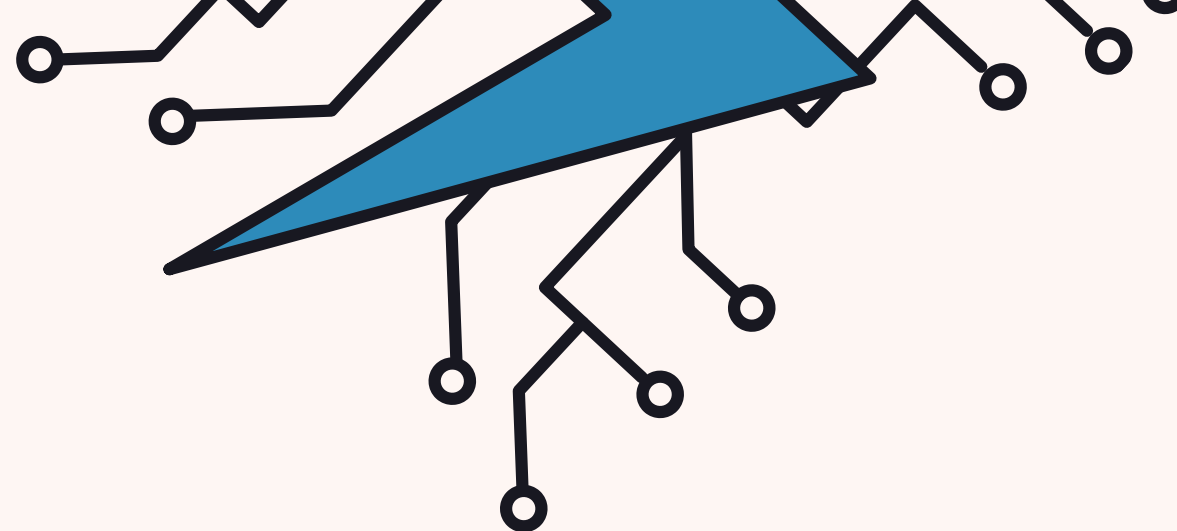
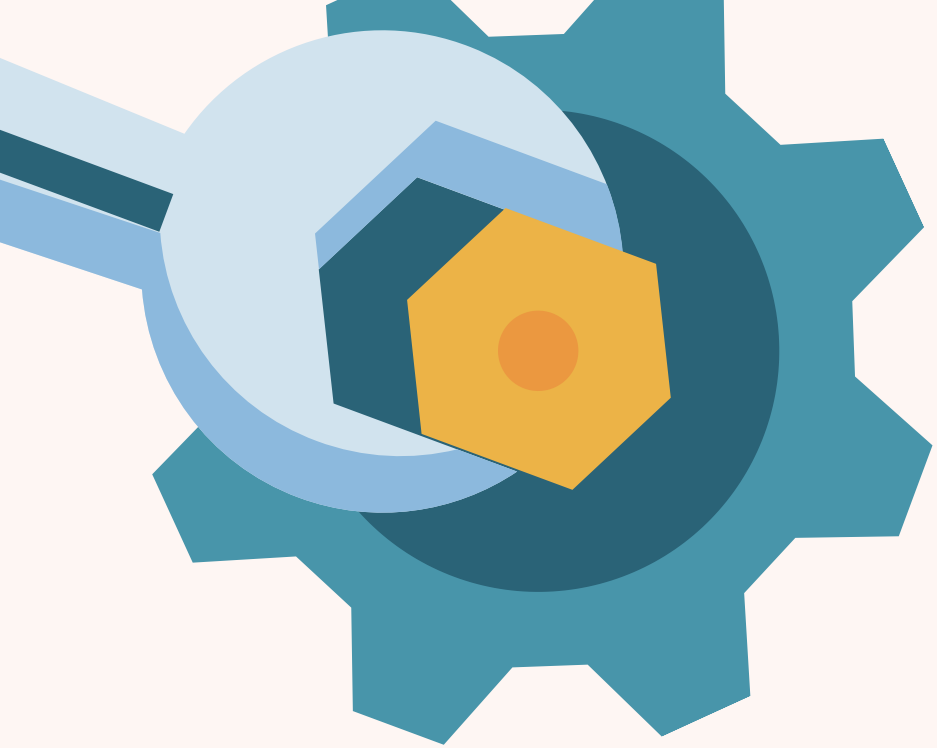
## Game Modes

- SPACE → Start
- H → Human mode
- A → AI mode
- ESC → Quit



# Conclusion

- The agent learned a clear strategy: move toward food.
- Q-learning outperformed the random policy significantly.
- Custom environment helped understand RL fundamentals.
- The trained Q-table captures the agent's learned policy and can be extended into future versions of the graphical game.
- Pygame visualization made learning behavior obvious and interactive.
- Project demonstrates successful integration of AI + game development + RL theory.



**Thank  
You**

