



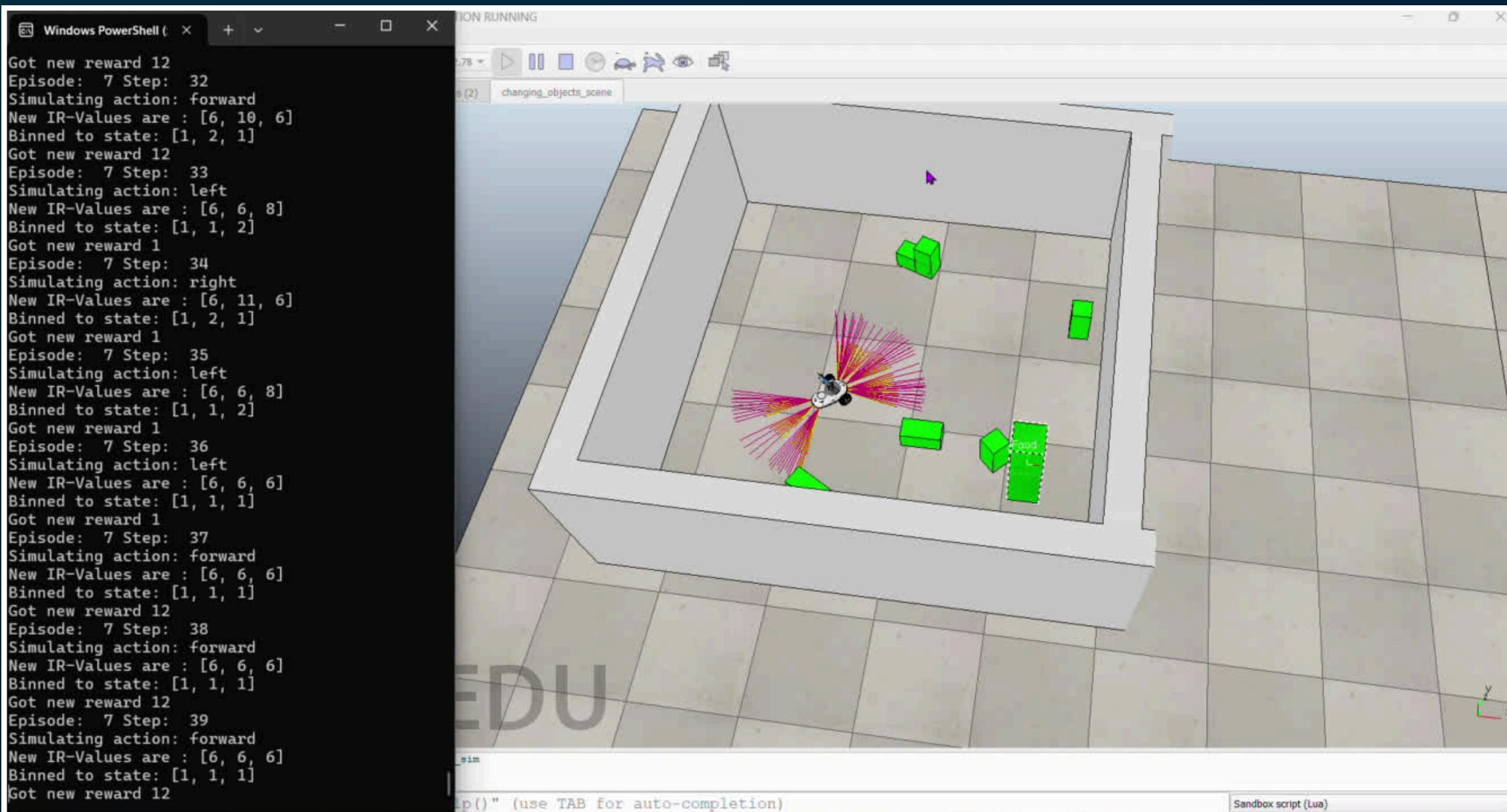
TASK 1 - OBSTACLE AVOIDANCE

LEARNING MACHINES Robobo

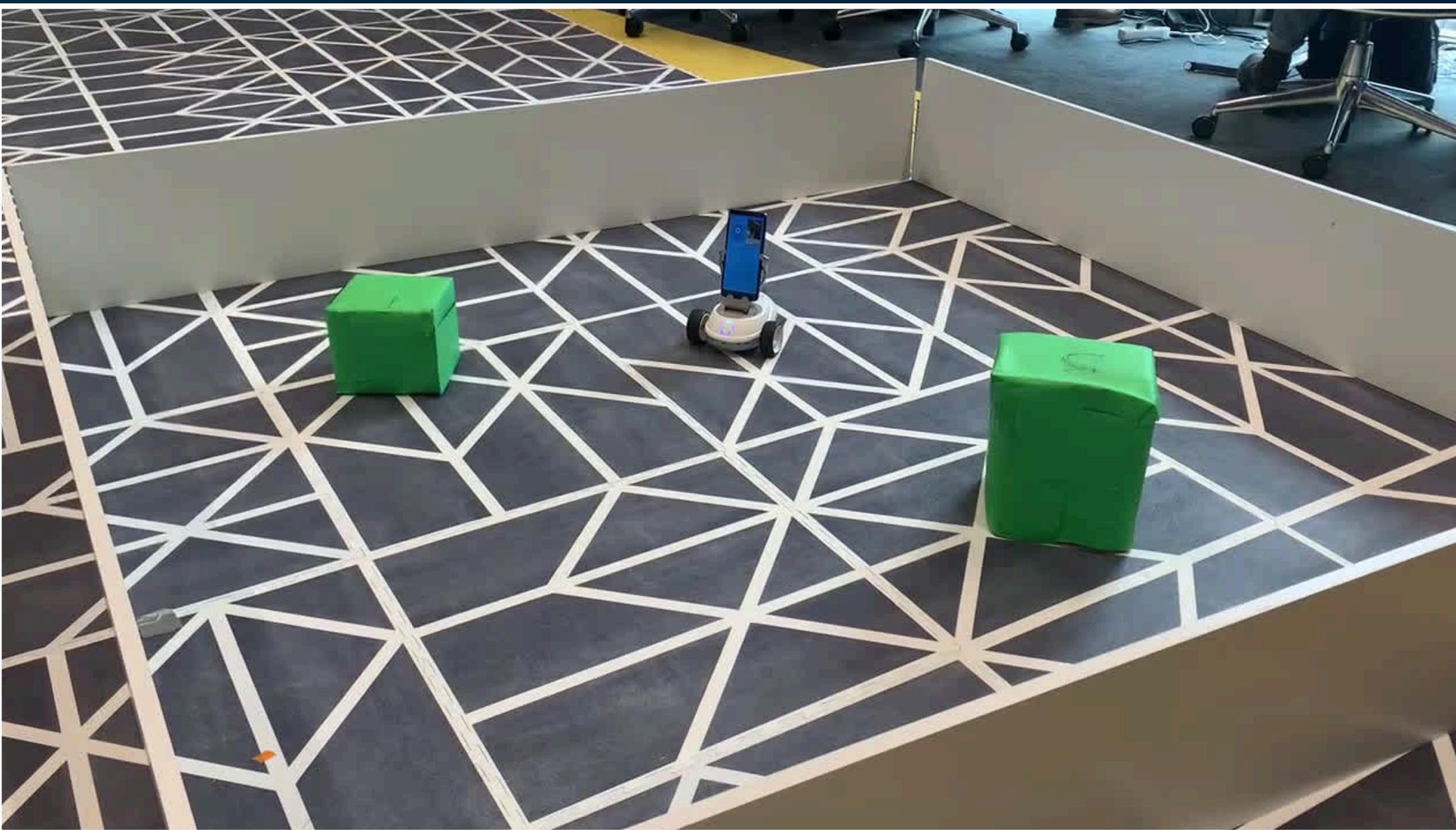
GROUP 14

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SIMULATION DEMO



HARDWARE DEMO



PROBLEM & MOTIVATION

- **Objective:** Train a robot to navigate an environment filled with static obstacles efficiently and with minimal collisions.
- **Challenges:**
 - Navigating cluttered spaces demands advanced sensory and processing skills.
 - Requires quick-decision algorithms to prevent collisions and enable real-time reactions.
 - Ensure robust performance despite hardware and software constraints.
 - Operates within sensory and computational limits.



PROBLEM & MOTIVATION

- **Utility and Importance to AI Community:**
 - Pushes forward the capabilities of autonomous robots, in navigation and real-time processing.
 - Promotes research in AI on learning efficient navigation strategies, sensory integration, and obstacle avoidance.
 - Development of more sophisticated decision-making models that can generalize from simulation to real-world scenarios.
 - Insights gained can benefit other fields such as autonomous driving, drone operation, and even video game AI.



METHODOLOGY

- **Q-learning**: A model-free Reinforcement Learning algorithm
 - *Purpose*: It helps the agent/robot to learn making optimal decisions by estimating the utility of actions in given states.
 - *Key Components*:
 - Q-values: state-action value function.
 - Q-table: Represents the expected future rewards for an action taken in a given state.
 - State: The current conditions under which the robot is operating.
 - Action: A set of all possible actions the robot can take.
 - *Learning Process*:
 - Initializes Q-values : In our case 0.0
 - Uses the Q-values to guide actions and update them based on rewards received and future ones.



METHODOLOGY

- The Q-learning algorithm updates the Q-values with the following formula:

$$Q(s, a) = Q(s, a) + \alpha [R(s, a) + \gamma \max Q'(s', a') - Q(s, a)]$$

- *Sensing and Reality Gap:*
 - 3 Infrared (IR) sensors were used to perceive the environment : Front-Left, Front-Center, Front-Right
 - Binning Logic was used to simplify the state space for Q-learning:
 - Sensor readings: [15, 5, 5] → Discrete bins: [2, 1, 1]
 - Sensor readings: [50, 20, 5] → Discrete bins: [3, 2, 1]
 - Bin-values: 0 - ‘no detection or sensor error’, 1 - ‘detected far’, 2 - ‘detected close’, 3 - ‘collision’.
 - Different thresholds for simulation and hardware, due to Reality Gap



EXPERIMENTAL SETUP

- Three actions ('forward', 'left', and 'right') were used determined by sensor-based state readings.
- The '*Epsilon-Greedy Algorithm*' was used for action selection.
- 3 sensors were used: Front-far-Left, Front-Center, Front-far-Right.
- Different bin-thresholds were used for the simulation and the hardware ([4, 7, 25] [-1, 15, 100]).
- 4-6 bins were used per sensor. ([4, 7, 15, 30] [4, 7, 10, 15, 25])
- Up to 40 steps were used per episode.
- 100 episodes were used for training.
- An *epsilon* of 0.1 was used, allowing for 10% random action selection.
- A forward reward of 11, and a hitting penalty of -50 were used.
- *Training:*
 - Conducted in simulation.
- *Evaluation:*
 - Total rewards collected per episode to measure the effectiveness of navigational decisions.

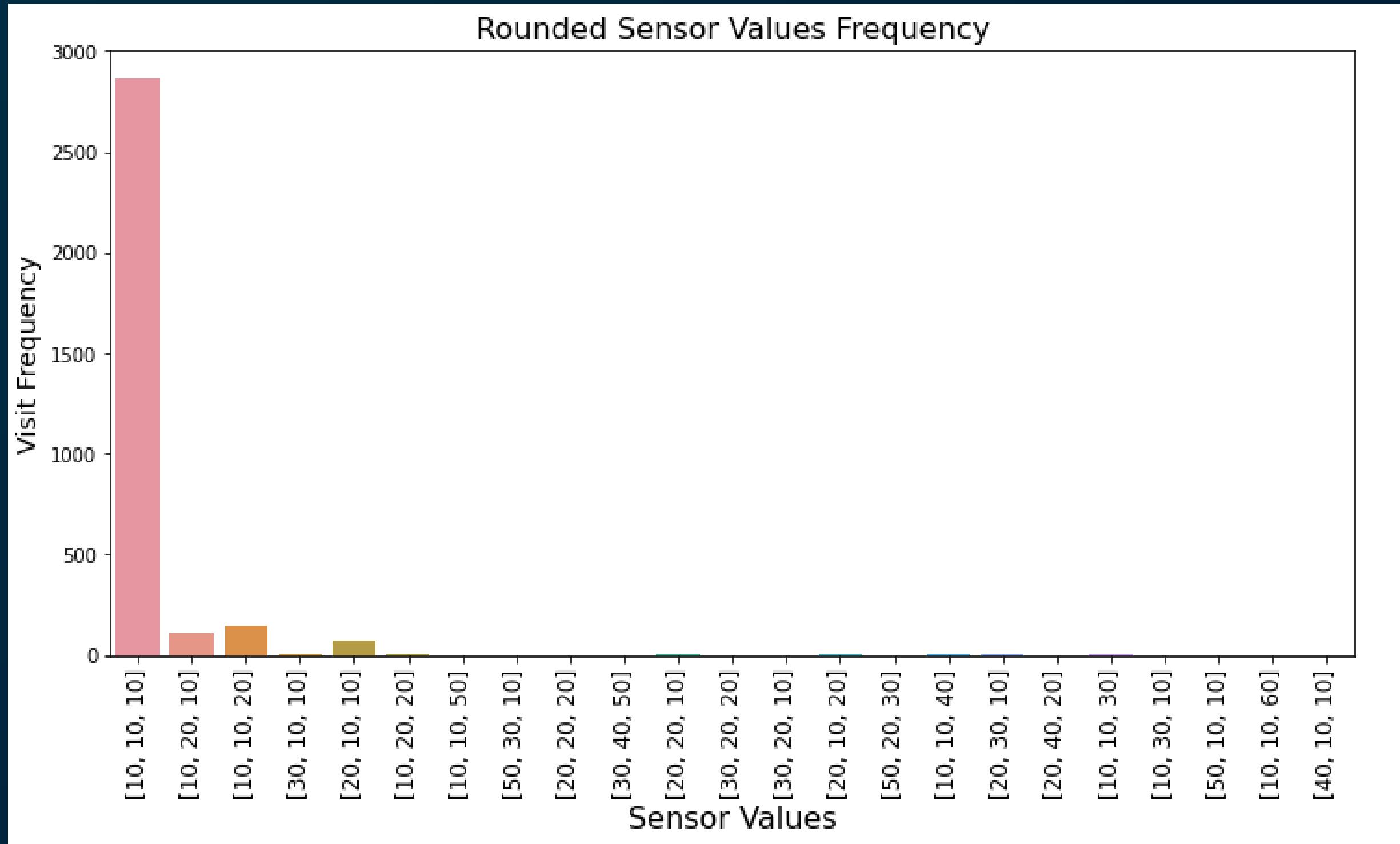


EXPERIMENTAL SETUP

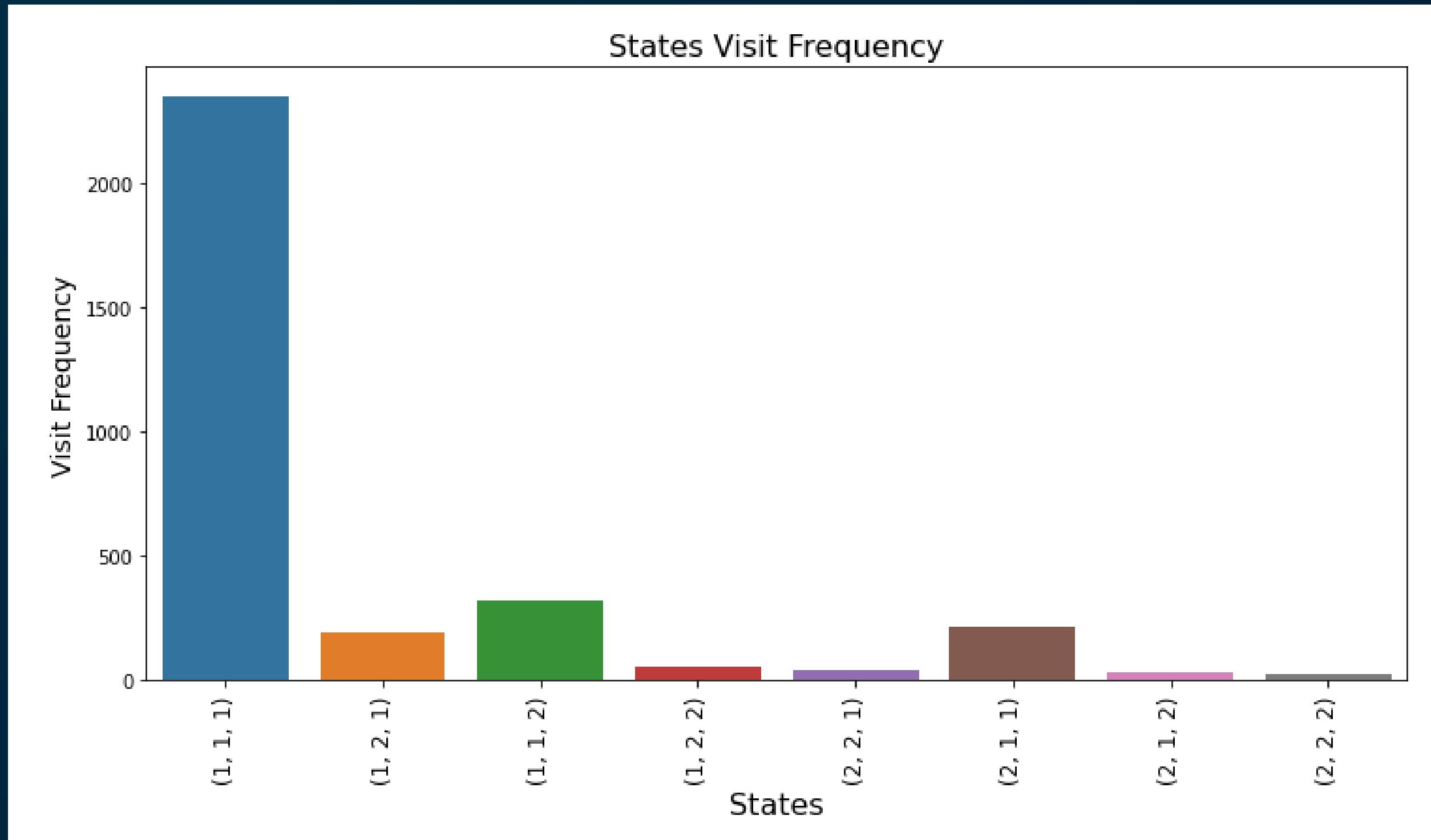
- **Challenges Encountered:** The robot always moved to the right, avoiding obstacles, due to a low default reward of 1, which encourages actions that prolong survival without hitting objects.
- **Solution Implemented:** We increased the reward for moving forward, pushing the robot to choose forward movements over other directions.



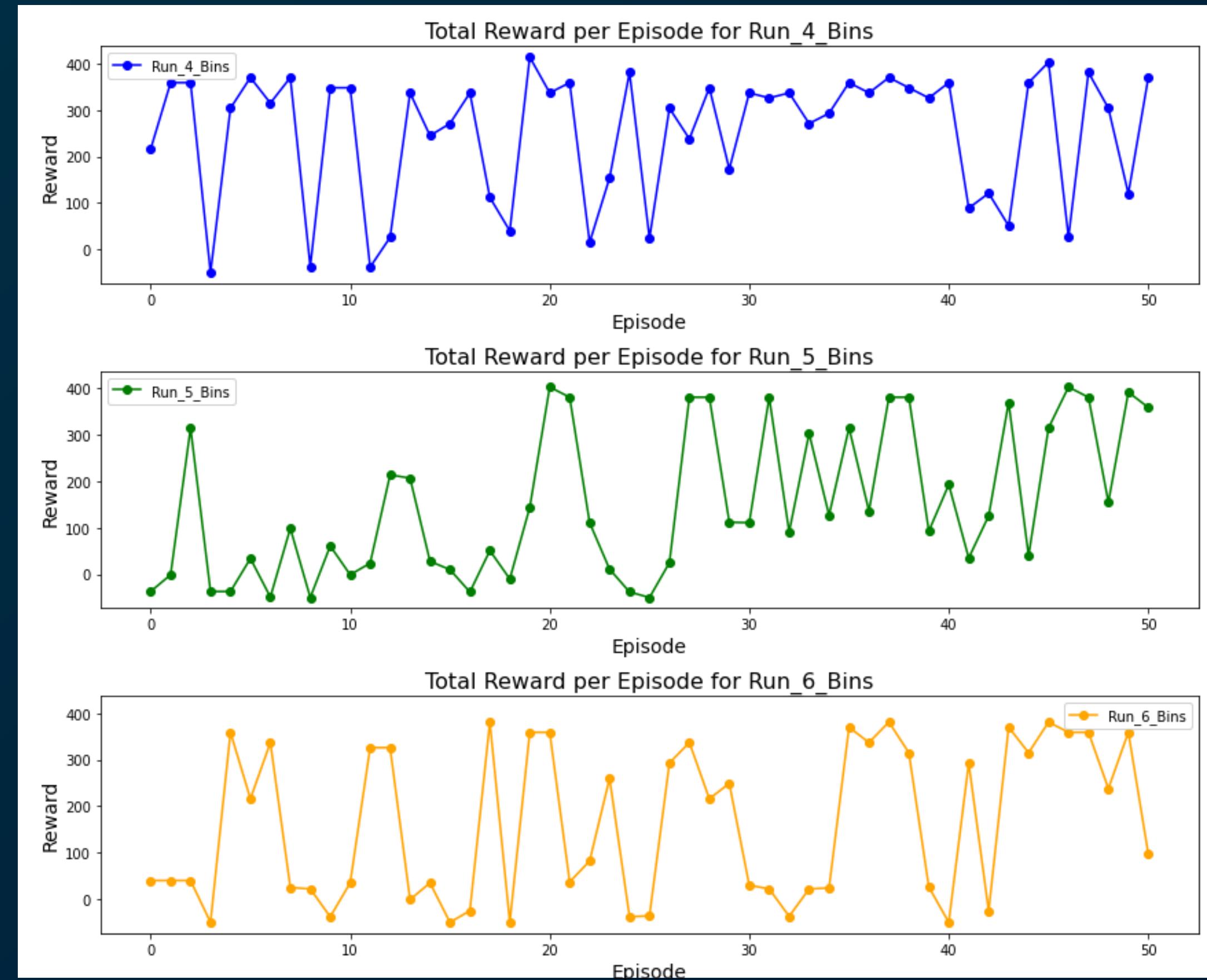
RESULTS: WHAT DO THE SENSOR DETECT?



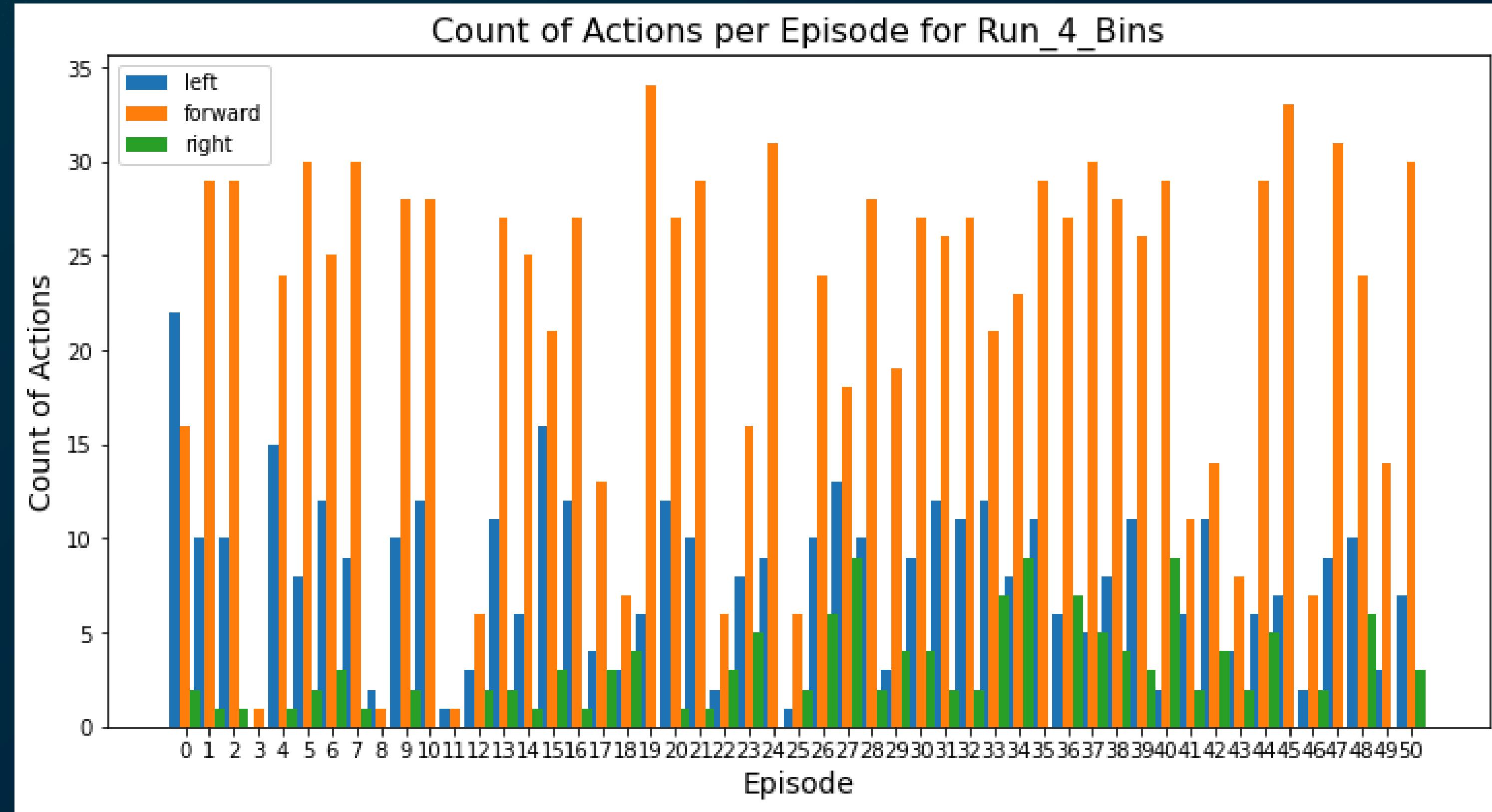
RESULTS: WHAT DO THE SENSOR DETECT?



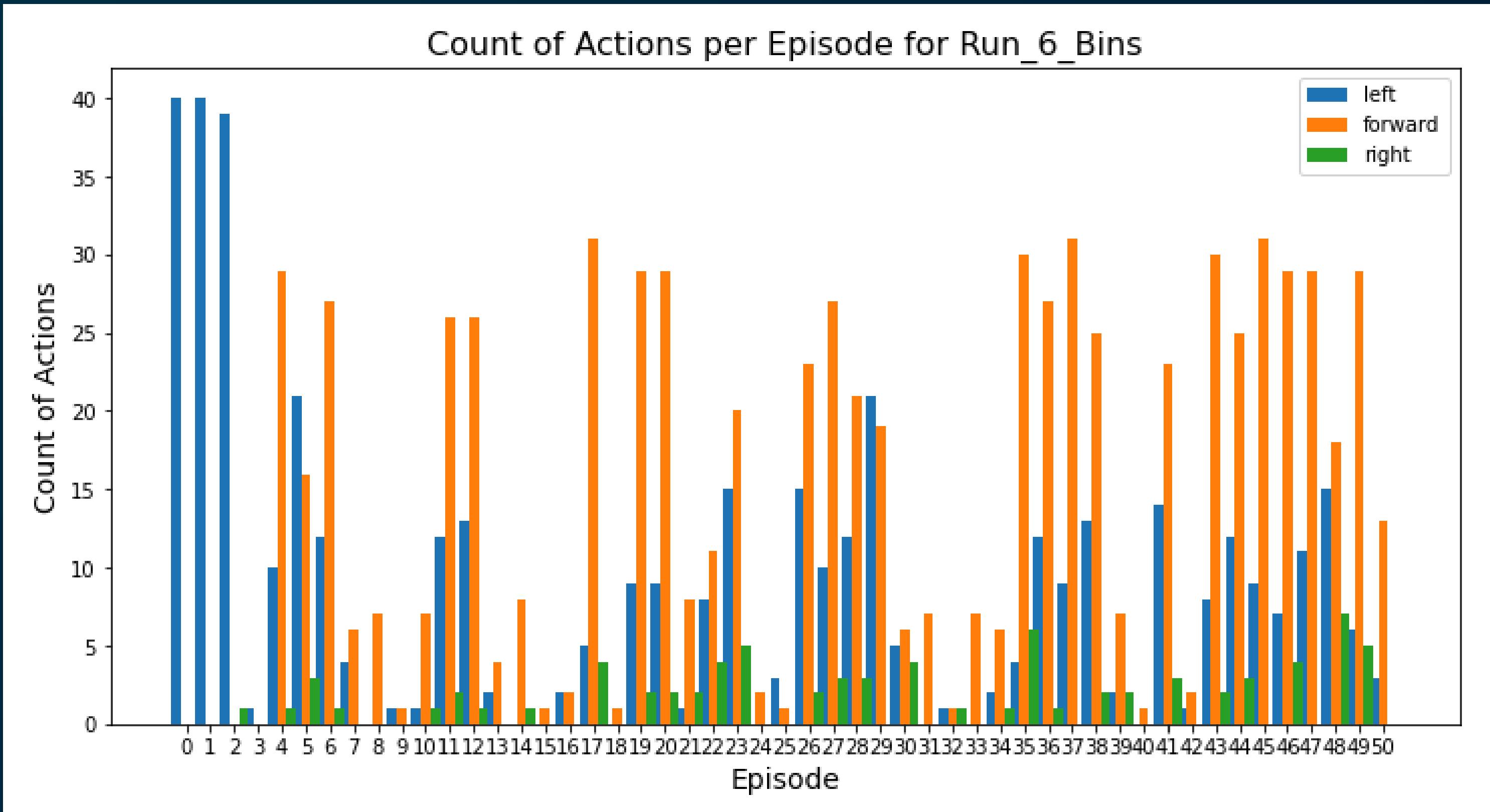
RESULTS: HOW FAST DO WE LEARN?



RESULTS: HOW FAST DO WE LEARN?



RESULTS: HOW FAST DO WE LEARN?



RESULTS: DO WE UNDERSTAND Q-TABLE?

(1, 1, 1)	[70.08844812904618, 83.85421854661962, 69.56212245613692]
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(1, 1, 2)	[74.96237752355954, 28.122589864263055, 12.049834933493845]
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(1, 2, 1)	[63.96763601338395, 6.562652192401206, 1.4003841897522982]
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(1, 2, 2)	[60.73889384420776, 4.030099707645284, -0.060311223026873306]
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(2, 1, 1)	[15.72534435158139, 37.157011168023246, 71.05373259919129]
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(2, 1, 2)	[46.2882571489996, 9.941255095388183, 5.57402016717459]
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(2, 2, 1)	[-0.44003591335158765, -4.691894377909125, 44.17709271334031]
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(2, 2, 2)	[18.03318946646317, -15.504303200000003, -2.5101325344578305]
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CONCLUSIONS

- The Robot learns to **not** hit anything in the first +-50 episodes.
- There is not really a difference between the number of bins chosen, 4 is good enough.
- Hardware works with selecting right Bin thresholds.
 - Could be done automatically by first calibrating sensors, then mapping to bin.
 - Too much time consuming.
- Future work:
 - Try to implement a Deep RL algorithm.



THANK YOU

QUESTIONS ???



CONTRIBUTION SHEET

- **Stergios:**

- Created the structure and content for the presentation slides.
- Created a new obstacle scene in CoppeliaSim.
- Experimented with the code for training the robot (action selection, binning logic, reward function).

- **Thijs:**

- Set up for initial code.
- Experimented with IR values.
- Experimented with reward function.
- Experimented with hardware.

- **Quirinus:**

- Improved on initial code, especially the usage of the right sensors, introducing constants in code.
- Created code for storing data while running.
- Created plots from saved data.



BUDDY-GROUP SUMMARY

- **Stergios:**

- Better understanding of how a team works.
- Diverse perspectives improved my ability to see multiple sides of a situation before making decisions.
- Learned how to implement a reinforcement learning algorithm to a real-world scenario.
- Learned more about the functionalities of the robot (navigating and sensing).

- **Thijs:**

- Diverse Perspectives.
- Learned practical techniques for minimizing the reality gap in simulations.

- **Quirinus:**

- Learned a lot from how to set up and work in coding projects like this.
- Got better understanding of using Git (not there yet haha).
- We started working together better with a plan and some task division.
- Learned about group behavior and interactions.

