**Adaptive Behaviour in Light-Seeking Organisms: A Simulation Study**

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This study explores the implementation and ability of a weight-based decision-making mechanism in a simulated environment where an artificial organism seeks out light sources of varying intensities. The primary aim was to demonstrate an adaptive system where the organism learns to preferentially navigate towards the most beneficial light source based on accumulated experiences. Utilizing the Pygame library for simulation and Python for data handling and visualization, the experiment was structured around a single organism equipped with energy parameters and a decision-making algorithm influenced by weight adjustments corresponding to the energy gains from different light sources. The methods involved simulating multiple light sources with distinct intensities and tracking the organism's decisions, movements, and energy levels. The organism's decision-making was guided by updated weights representing its learned preferences, which adjusted according to the energy benefits received from each light source. The simulation ran multiple iterations to observe patterns and adaptations over time. Key findings indicate that the organism successfully adapted its behaviour to increasingly Favor light sources that maximized its energy retention, demonstrating a basic form of learning through weight adjustments. This adaptation was quantified through the analysis of visit frequency, energy levels, and movement.

paths, illustrating a clear preference shift towards more advantageous light sources as the simulation progressed. The significance of this study lies in its contribution to understanding how simple adaptive mechanisms can be implemented in simulated environments to mimic learning behaviours. This research not only supports theories in adaptive systems but also provides a groundwork for more complex simulations where multiple agents interact within an environment, potentially leading to insights in fields such as robotics and artificial intelligence.

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# Introduction

Adaptive systems have been a subject of great interest in the fields of artificial life, robotics, and computational biology. These systems are characterized by their ability to change and adapt their behaviour in response to environmental stimuli, leading to the emergence of complex and intelligent behaviours (Holland, 1992). One fascinating example of adaptive behaviour in nature is the light-seeking behaviour exhibited by many organisms, from simple bacteria to more complex invertebrates and vertebrates (Jekely, 2009). This behaviour allows organisms to navigate their environment, find food, and avoid predators by detecting and responding to light stimuli.

In this study, we investigate the principles of adaptive systems and light-seeking behaviour through a simulated organism in a virtual environment. Our aim is to develop a model that captures the essential features of light-seeking behaviour and demonstrate the process of adaptation through a learning mechanism. By understanding the underlying mechanisms of such adaptive behaviours, we can gain insights into the evolution and functioning of biological systems, as well as develop more efficient and robust algorithms for artificial systems (Floreano & Mattiussi, 2008).

The simulated organism in our experiment is inspired by the concept of Braitenberg vehicles (Braitenberg, 1986), which are simple agents that exhibit complex behaviour based on sensory-motor connections. In this study the organism's behaviour is governed by a weighted decision-making process, where the weights assigned to different light sources determine the organism's attraction or aversion towards them. A key feature of our model is the incorporation of a learning mechanism, which enables the organism to adapt its weights based on the outcomes of its actions, similar to reinforcement learning (Sutton & Barto, 2018).

To evaluate the adaptivity and performance of our simulated organism, we employ a variety of data collection and analysis techniques. These include tracking the organism's energy levels and movement paths over time. By visualizing and analysing these data, we can assess the organism's ability to learn and adapt to its environment.

Our experimental setup builds upon previous work in the field of adaptive systems and artificial life. For example, Beer (1996) developed a model of a dynamical neural network that evolved to exhibit minimally cognitive behaviour, such as approaching and avoiding light sources. Similarly, Nolfi and Floreano (2000) explored the evolution of adaptive behaviour in simulated and physical robots using evolutionary algorithms. Our work extends these ideas by incorporating a learning mechanism and focusing on the specific cases of light-seeking behaviour.

Overall, this study presents a simulated organism that exhibits adaptive light-seeking behaviour through a weighted decision-making process and a learning mechanism. By investigating the principles of adaptation and learning in this context, we aim to contribute to the understanding of adaptive systems and their applications in artificial life and robotics. In the method section will describe the methods used in our experiment, present the results and analyses of the simulated organism's behaviour, and discuss the implications and future directions of this research.

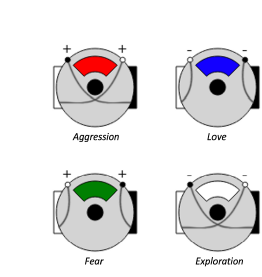
# PHOTOTACTIC BEHAVIOUR

The movement of an organism in response to light, is a well-studied phenomenon in biology and has been a source of inspiration for many artificial life and robotics projects. Organisms exhibiting positive phototaxis move towards light sources, while those displaying negative phototaxis move away from light (jékely, 2009). This behavior is observed in a wide range of organisms, from single-celled bacteria to more complex invertebrates and vertebrates (randel & jékely, 2016). The study of phototaxis has provided insights into the mechanisms of sensory perception, decision-making, and locomotion in biological systems (ward et al., 2008).

In the context of our project, understanding phototactic behavior is crucial for designing and analyzing our simulated light-seeking organism. Many researchers have explored the principles of phototaxis using computational models and robotics which includes braitenberg's seminal work on vehicles demonstrated how simple sensory-motor connections can give rise to complex phototactic behavior. Similarly, dave lambrinos and colleagues (2000) developed a neural network model of phototaxis in the marine mollusk hermissenda, showcasing the role of learning in adapting to different light conditions. These studies have provided a foundation for this project, guiding the design of our organism's sensory system, decision-making process, and learning mechanism.

# INFLUENCE OF BREIGHTENBERGS VEHICLES.

Braitenberg's vehicles have been a significant influence on our project, as they demonstrate the principles of adaptive behaviour and sensory-motor coordination in a simple and intuitive way. The light-seeking organism in our simulation can be seen as an extension of these basic vehicles, with slightly complex sensory systems, decision-making processes, and learning mechanisms. By studying Braitenberg's vehicles, we can better understand the building blocks of adaptive behaviour and how they can be combined to create more complex systems.



**Figure 1.1: Illustrations of the four vehicles of**

**type 2 and 3 as described by Braitenberg: Aggression,**

**Love, Fear and Exploration. The illustrations**

**were taken from de Weerd [2016].**

The vehicles in the image are labelled as Aggression, Love, Fear, and Exploration. Each vehicle has two sensors (represented by the + and - signs) and two motors (represented by the circles). The connections between the sensors and motors determine the vehicle's behaviour. For example, the Aggression vehicle has excitatory connections from its sensors to the motors on the same side, causing it to accelerate towards the stimulus. In contrast, the Fear vehicle has inhibitory connections from its sensors to the motors on the same side, causing it to turn away from the stimulus, which mirror the biological principles of positive and negative phototaxis. In our project, we have incorporated the ideas of sensory-motor connections and stimulus-response behaviours inspired by Braitenberg's vehicles. Our simulated organism uses the behaviour light sensors to detect the intensity and direction of light sources in its environment, and its motors allow it to move towards or away from these stimuli. This design draws directly from the principles illustrated by Braitenberg's vehicles.

# USE OF SIMULATION

In exploring the subject of adaptive systems, particularly within the constraints of time and resource availability, simulation emerges as an indispensable tool (Cliff et al., 1993). Its application extends beyond mere feasibility, offering a sandbox for hypothesizing, experimenting, and observing the behaviors of complex systems in a compressed timeline. In the context of this project, simulations facilitated a nuanced examination of the dynamics between light-seeking organisms and their environment, providing valuable insights that would be arduous, if not impossible, to glean from real-world experimentation. Simulated environments allowed for rapid iteration and testing of hypotheses, revealing patterns and principles of adaptivity applicable to both artificial and natural systems. As such, this study's application of simulation adheres to the frameworks and principles established by Cliff et al., underscoring the validity and reliability of the insights derived from such methods.

# WEIGHT BASED ADAPTIVE LEARNING.

In our simulation, we have implemented a weight-based learning mechanism that allows the simulated organism to adapt its behaviour based on its experiences. This learning mechanism is inspired by the principles of reinforcement learning (Sutton & Barto, 2018), where an agent learns to make decisions by receiving rewards or punishments from its environment. In our case, the organism's sensors are connected to its motors through weighted connections, which determine the strength and direction of the influence of sensory input on motor output. Initially, these weights are set based on the intensity of the light sources, creating a bias towards brighter stimuli. As the organism interacts with its environment, the learning mechanism adjusts these weights based on the outcomes of the organism's actions. Specifically, when the organism reaches a light source, the weights associated with that source are increased, reinforcing the behaviour that led to the positive outcome. This weight update is governed by a learning rate, which determines the speed and magnitude of the adaptation. Over time, this process allows the organism to learn and adapt its behaviour, prioritizing actions that lead to higher energy gains. This weight-based learning mechanism is a simplified version of the more complex learning algorithms used in artificial neural networks and deep reinforcement learning (Goodfellow et al., 2016), but it effectively demonstrates the key principles of adaptive behaviour and decision-making.

# METHODS.

## Simulation Environment:

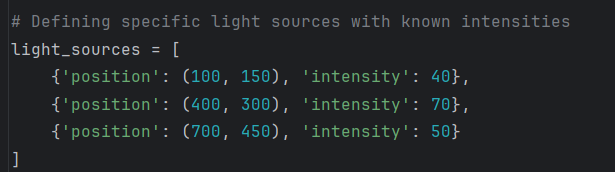
The simulated environment is a 2D virtual space where the light-seeking organism exists and interacts with light sources.

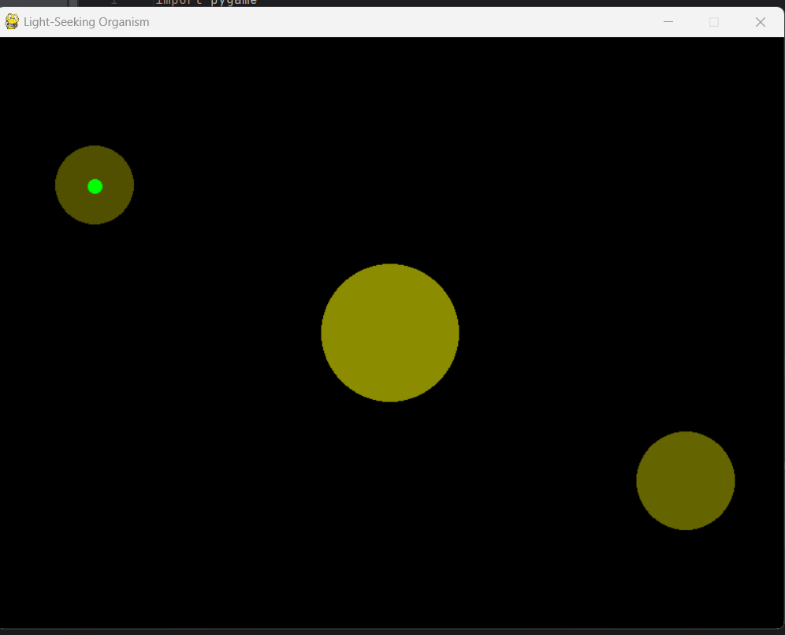
I have designed the environment with the help of python Libraries like, Pygame, Random, Matplotlib and math. The environment has a size of 800 pixels wide and 600 pixels high, defined by the variables width and height. The boundary conditions are not explicitly specified in the code, but the organism's movement is limited to the defined width and height of the environment.

A screen shot of a computer program

Description automatically generated

The environment contains three light sources with predefined positions and intensities. The light sources are represented as dictionaries in the light\_sources list, each with a 'position' (x, y) and an 'intensity' value.





**Figure.2: Screenshot of the simulating environment with light sources (yellow) of different intensities at different positions in the environment and an organism (Green) close to the light source.**

## Organism Model.

We will be studying the behaviour of one unicellular organism particularly (to make our analysis clear and evident) in the environment.

The organism is equipped with simulated light sensors that detect the intensity and direction of light sources in the environment, mirroring the real biological behaviour of light seeking unicellular organisms which tend to move in the direction of the light source which attracts the more the one with high intensity (Robert M. Macnab, Behavioural adaptation in prokaryotes). The sensors are not explicitly modelled in the code, but their functionality is implicitly represented through the calculations of distances between the organism and the light sources. The organism's perception of light is based on the distance between its position and each light source's position.

The organism has a simple motion model that allows it to move in the 2D environment. The organism's movement is controlled by updating its position (organism.centerx and organism.centery) based on the direction and distance to the selected light source. The speed of movement is determined by the organism\_speed variable.

## Energy Model:

I further implemented an Energy model in the simulation where organism's energy is represented by the organism\_energy variable. The initial energy level is set to 100. The organism's energy is depleted by a fixed amount (energy\_decay) at each step of the simulation with movement. When the organism reaches a light source (i.e., the distance to the light source is less than its intensity), its energy is replenished by an amount proportional to the light source's intensity multiplied by an energy\_gain factor.

To make the depletion of energy clearly evident in the simulation, I did a color code such that the organisms color change from green to red with its movement towards light, and turns back to green when it successfully reaches the light signifying the energy gain. Unlucky organisms which fail to reach the light source within time lose its energy completely and die. In this scenario the organism in our simulation turns red and stops its movement.



Figure:3. Screenshot from the simulation, depicting organisms’ low energy level (red)

## Behavioral Algorithm

The organism's decision-making process is based on the weighted distances to the light sources. The algorithm is designed in such a way that the organism tends to choose the closest light source from its origin (which is random with every run). The organism calculates the weighted distance to each light source by dividing the squared distance by the corresponding weight stored in the weights dictionary of our Python code. The light source with the smallest weighted distance is selected as the target for movement. This decision-making process is inspired by the concept of weighted decision-making in reinforcement learning (Sutton & Barto, 2018) and also the inverse square law of light intensity. (Ashdown, 2018).

## Learning Mechanism:

The organism's learning is implemented through a simple weight update mechanism. The weights associated with each light source are initially set based on the light source's intensity, creating a bias towards brighter light sources. When the organism successfully reaches a light source, the weight associated with that light source is increased by a value proportional to the light source's intensity multiplied by a learning\_rate factor. This reinforcement mechanism tends to increase the organism's preference for light sources that have been previously reached, similar to the reward-based learning in reinforcement learning algorithms (Sutton & Barto, 2018) and the concept of associative learning in animal behavior (Pearce, 2013)

## Learning rate

In our project, the learning factor, denoted as learning\_rate in the code, is a constant value that determines the rate at which the weights associated with the light sources are updated during the learning process. The learning\_rate is set to 0.1 in the code.

When the organism successfully reaches a light source, the weight of that light source is updated using the following code:

weights[tuple(closest\_light['position'])] += learning\_rate \* closest\_light['intensity']

The learning\_rate controls the magnitude of the weight update. A higher learning\_rate value will result in larger weight updates, causing the organism to adapt its preferences more quickly. Conversely, a lower learning\_rate value will lead to smaller weight updates, resulting in a slower adaptation process.

The learning\_rate value of 0.1 used in our code was chosen empirically to strike a balance between quick adaptation and stable learning.

## Simulation Process

The initial conditions for each simulation run are set by initializing the organism's position randomly within the environment's boundaries using random.randint() function. The organism's energy level is set to 100 at the beginning of each run.

The main loop of the simulation is executed while the running variable is True. At each step, the organism's position, energy level, and distance to light sources are updated based on the behavioral algorithm described above. The organism's movement is simulated by updating its position based on the direction and distance to the selected light source. The organism's energy is depleted by the energy\_decay amount and replenished if it reaches a light source. The simulation continues until the organism's energy reaches zero or the user closes the simulation window.

## Data Collection and Analysis

Recording: During each simulation run, various data points are collected and stored in lists and dictionaries. The energy\_levels list records the organism's energy level at each step. The distances\_to\_lights dictionary stores the distances between the organism and each light source at each step. The visits\_to\_lights dictionary keeps track of the number of times the organism reaches each light source. The energy\_gain\_from\_lights dictionary records the energy gained by the organism from each light source. The movement\_paths list stores the organism's position at each step, forming a trajectory of its movement.

Analysis: The collected data is analyzed and visualized using the Matplotlib library. The energy levels over time, distances to light sources, movement paths, light source selection counts, and weight history are plotted to evaluate the organism's adaptive behavior. These visualizations help in assessing the organism's performance, energy management, and preferences for different light sources.

## Libraries and their utility:

Pygame: Used for creating the simulation environment, handling user input, and visualizing the organism and light sources.

Random: Used for generating random initial positions for the organism.

Math: Used for mathematical calculations

Matplotlib: Used for data visualization by plotting graphs.

The main variable parameters used in the simulation are:

width and height: The dimensions of the simulation environment (800 and 600 pixels, respectively).

organism\_size: The size of the organism (15 pixels).

organism\_speed: The speed at which the organism moves (2 pixels per step).

energy\_decay: The amount of energy the organism loses at each step (1 unit).

energy\_gain: The factor that determines the energy gained when reaching a light source (0.5).

learning\_rate: The rate at which the weights associated with light sources are updated during learning (0.1).

light\_sources: The list of light sources with their positions and intensities.

Pseudo Code  
Initialize Pygame

Set up the display with width and height

Define colors

Define organism properties (size, speed, initial energy)

Define the color\_from\_intensity function to generate colors based on intensity

Define specific light sources with known intensities and positions

Update the light sources with their colors using the color\_from\_intensity function

Initialize a single organism with random position

Define energy decay and gain constants

Initialize weights with a bias towards intensity

Initialize data collection lists and dictionaries

Define the learning rate

Initialize weight history dictionary

While the simulation is running:

Handle events (quit event)

Append the current position to movement\_paths

Append the current energy level to energy\_levels

If the organism has energy:

Calculate the weighted distance for each light source

Select the light source with the smallest weighted distance

Calculate the direction and distance to the selected light source

If the distance is greater than zero:

Decrease the organism's energy by the energy decay constant

Move the organism towards the selected light source

If the distance is less than the selected light source's intensity:

Increase the organism's energy by the intensity multiplied by the energy gain constant

Increase the weight for the selected light source using the learning rate

Increment the selection count for the selected light source

Append the current weights to the weight history dictionary

If the organism's energy is less than or equal to zero:

Set the organism's energy and speed to zero

Fill the screen with black color

Draw the light sources on the screen

Calculate the organism's color based on its energy level

Draw the organism on the screen

Update the display

Regulate the frame rate

Quit Pygame

Plot the energy levels over time

Plot the movement path of the organism

Plot the histogram of light source selections

Plot the weight history for each light source

# RESULTS AND ANALYSIS.

1. In the simulation, When the organism fails to reach a light source, due to depletion of energy, the colour of the organism turns red and its movement stops.
2. When the organism successfully reaches a light source and gains energy, it’s a success.

we collected various data points to analyze the organism's behavior and adaptability.

Let us discuss the behaviour of an organism which successfully chose the light source at position (400,300) which has the highest intensity of 70. The plotted graphs and their significance are as follows:

A screenshot of a computer

Description automatically generated

**Figure.4: organism which successfully chose the light source at position (400,300)**

## Energy Levels Over Time:

The plot of energy levels over time shows how the organism's energy fluctuates throughout the simulation.

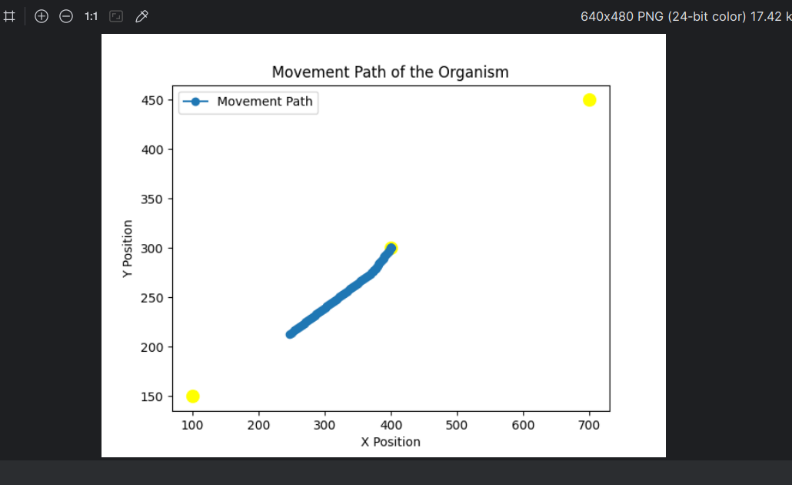
A graph on a computer screen

Description automatically generated

**Figure.5: Picture depicts the energy over time of the light seeking organism in our simulation run.**

The graph shows that the organism starts with an initial energy level of around 100 units. This initial energy level sets the baseline for the organism's energy dynamics throughout the simulation. A gradual decrease in energy level is seen during the movement of organism until A stable or increasing energy level trend indicates that the organism has successfully navigated towards light sources and replenishing its energy. This result is important to assess the organism's survival ability and the effectiveness of its decision-making and learning mechanisms.

## Movement Path of the Organism:

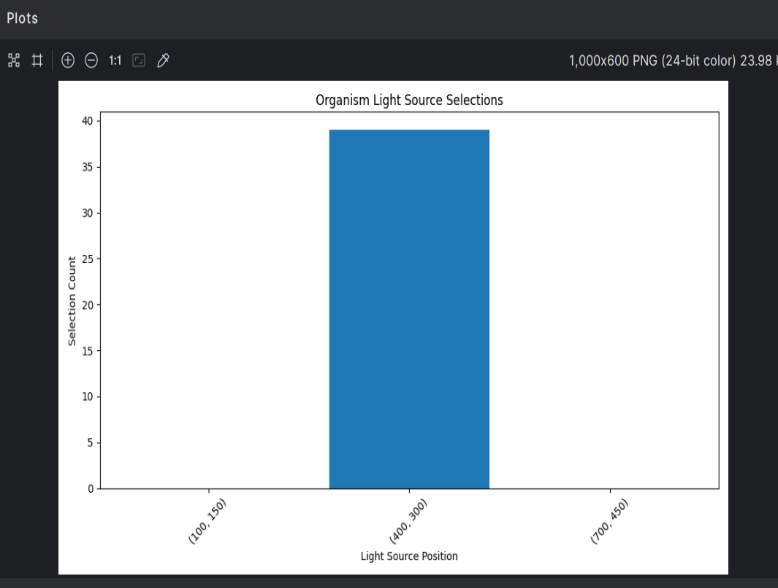


**Figure.6: Depiction of movement path of the organism in the environment**

The plot of the organism's movement path provides a representation of its trajectory throughout the simulation. It reveals the organism's exploration patterns and how it navigates the environment in relation to the light sources.The movement path can indicate whether the organism is efficiently moving towards the light sources or exhibiting any peculiar or inefficient behaviors.This result is important to understand the organism's navigation strategies and identify any potential limitations or areas for improvement.

## Organism Light Source Selections:

The histogram of light source selections shows the frequency with which the organism chooses each light source during the simulation. It provides insights into the organism's preferences and decision-making process.



**Figure.7: The bar graph indicates the organisms most frequently selected the light source at (400,300) compared to the other two light sources.**

## Weights of Light Sources Over Time:

The plot of the weights of light sources over time is crucial ro understand as it illustrates how the organism evolves throughout the simulation. It shows how the weights associated with each light source change based on the organism's interactions and the learning mechanism. increasing weight trends for frequently visited light sources demonstrate the organism's ability to reinforce its preferences and adapt its behaviour. This result helps us understand the dynamics of the organism's learning process and how it shapes its decision-making over time.

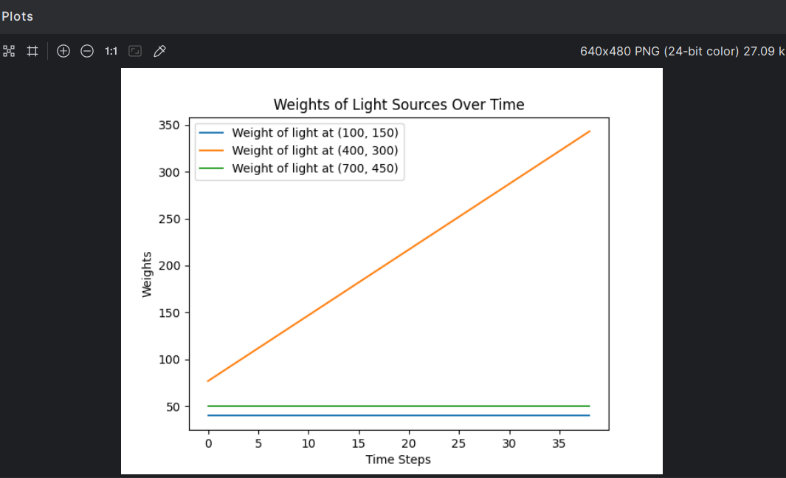


Figure.8: Graph of weights over time.

The graph shows a gradual increase in the weights of the light sources over time. This indicates that the organism is learning and adapting its preferences based on its interactions with the light sources. As the simulation progresses, the organism assigns higher weights to the light sources that it has successfully reached and gained energy from.

The analysis of these results collectively provides a comprehensive understanding of the organism's adaptive behaviour in the light-seeking task. It allows us to assess the effectiveness of the organism's decision-making, navigation, and learning capabilities. By examining the energy levels, distances, movement paths, light source selections, and weight evolution, we can identify patterns, trends, and potential areas for improvement in the organism's behaviour. Moreover, these results serve as a foundation for comparing different parameter settings, such as the learning rate, or for evaluating the impact of modifications to the simulation environment or the organism's architecture. They enable us to draw conclusions about the organism's adaptability and performance, and to make informed decisions for further enhancements or optimizations.

Overall, the simulation results validate the effectiveness of the implemented decision-making, learning, and adaptation mechanisms. The organism's ability to survive, navigate, and optimize its behaviour in the given environment demonstrates the successful realization of our goals. These findings contribute to our understanding of adaptive systems and their potential applications in artificial life and robotics.

# DISCUSSION

The current implementation of the light-seeking organism simulation demonstrates the basic principles of adaptation and learning in an artificial system. However, there are several avenues for future enhancements and the incorporation of more complex learning mechanisms.

One potential enhancement is the integration of reinforcement learning algorithms, such as Q-learning which can enable the organism to learn optimal policies for navigating the environment and maximizing its energy gains. These algorithms can handle more complex state spaces and reward structures, allowing for more sophisticated decision-making and adaptation.

Another avenue for improvement is the incorporation of neural networks or deep learning techniques. By utilizing neural networks as the underlying decision-making and learning mechanism, the organism can learn more complex patterns and representations of the environment. Deep reinforcement learning, combining deep neural networks with reinforcement learning, can enable the organism to handle high-dimensional sensory inputs and learn more advanced strategies.

Furthermore, the simulation environment can be extended to include more complex features, such as obstacles, dynamic light sources, or multiple organisms interacting with each other. These additions can introduce new challenges and opportunities for adaptation, requiring the development of more advanced learning mechanisms and coordination strategies.

# CONCLUSION

The light-seeking organism simulation project serves as a foundation for exploring the principles of adaptation and learning in artificial systems. The current implementation demonstrates the effectiveness of simple decision-making and learning mechanisms in enabling the organism to survive and optimize its behaviour in a basic environment.

However, the project opens up numerous possibilities for future enhancements and the incorporation of more complex learning mechanisms. By integrating reinforcement learning algorithms, neural networks, or deep learning techniques, the organism's decision-making and adaptation capabilities can be significantly enhanced. These advancements can enable the organism to handle more complex environments, learn optimal policies, and exhibit more sophisticated behaviours.

Moreover, extending the simulation environment to include additional features and challenges can further push the boundaries of adaptive systems research. The development of advanced learning mechanisms and coordination strategies can pave the way for the creation of more intelligent and autonomous artificial systems.

In conclusion, this project provides a promising starting point for exploring the vast potential of adaptive systems and learning mechanisms. Future research and development in this area can lead to the creation of intelligent agents capable of adapting to complex real-world environments and solving challenging problems in various domains, from robotics and autonomous systems to artificial intelligence and beyond.

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