Raynoid Synthetica: An Implementable Organoid Intelligence Model Without Cellular Response to External Input h(I(t)) = ReLU(I(t) · WI + bI)

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1 Introduction

The Raynoid Synthetica model provides a mathematical framework to simulate the intelligence of organoids. It bridges the gap between traditional artificial neural networks and biological systems.

2 Model Components

2.1 Cellular State

Each cell's state is represented as a continuous value ranging from 0 to 1, denoted as c_i. The global state is given by:

$$C = [c_1, c_2, \ldots, c_n]$$

for n cells in the organoid.

2.2 Synaptic Strengths

Each connection (or synapse) between cells i and j has a strength represented by s_{ij}. The strength matrix is:

$$S = \{s_{ij}\}$$

where $s_{ij} \in [-1, 1]$.

2.3 External Inputs

External stimuli at time t is represented by:

$$I(t) = [I_1(t), I_2(t), \ldots, I_n(t)]$$

2.4 Activation Function

The activation of cell i at time t is:

$$a_i(t) = \sigma\left(\sum_j c_j(t) \times s_{ij} + I_i(t)\right)$$

where σ is a sigmoid function ensuring the activation stays between 0 and 1.

2.5 Evolution Over Time

The state and synaptic strengths are updated as:

$$c_i(t+1) = (1-\lambda)c_i(t) + \lambda a_i(t)$$
$$s_{ij}(t+1) = s_{ij}(t) + \eta(a_i(t) - a_j(t)) \times (a_i(t) + a_j(t))$$

where λ is the cellular update rate and η is the synaptic learning rate.

2.6 Output Function

The global output of the organoid at time t is:

$$O(t) = \sum_i c_i(t)$$

2.7 Objective

For a known set of inputs and outputs, the goal is to evolve C and S to minimize the difference between $O(t)$ and the desired output $D(t)$. Given a known set of inputs and desired outputs, the objective is to evolve the cellular states C and synaptic strengths S to ensure that the global output $O(t)$ closely matches the desired output $D(t)$ for each respective input at time t.

Mathematically, the objective function can be defined as:

$$J(t) = \frac{1}{2}\left(O(t) - D(t)\right)^2$$

Where:

- $O(t)$ is the global output of the organoid at time t, calculated as $O(t) = \sum_i c_i(t)$.
- $D(t)$ is the desired output at time t.

The training process seeks to minimize the objective function $J(t)$ over all time steps.

2.8 Training Mechanism

The training process involves:

1. Presenting $I(t)$ to the organoid model.
2. Calculating $a_i(t)$ for all cells.
3. Updating $c_i(t+1)$ and $s_{ij}(t+1)$ for all cells and synapses.
4. Comparing $O(t)$ to $D(t)$ and adjusting parameters (λ, η) to minimize differences over iterations.

3 Raynoid Synthetica Algorithm

1. **Initialization**:
   - Define n cells with states c_i in range [0, 1].
   - Define synaptic strengths s_{ij} between cells in range [-1, 1].
   - Set cellular update rate λ and synaptic learning rate η.
2. **Input Presentation**:
   - Provide external stimuli $I(t)$ to the organoid model.
3. **Activation Computation**:
   - For each cell i, compute:

   $$a_i(t) = \sigma\left(\sum_j c_j(t) \times s_{ij} + I_i(t)\right)$$

   where σ is a sigmoid function.
4. **State & Synapse Update**:
   - For each cell i, update:

   $$c_i(t+1) = (1-\lambda)c_i(t) + \lambda a_i(t)$$

   - For each synapse s_{ij}, update:

   $$s_{ij}(t+1) = s_{ij}(t) + \eta(a_i(t) - a_j(t)) \times (a_i(t) + a_j(t))$$
5. **Output Computation**:
   - Compute global output as:

   $$O(t) = \sum_i c_i(t)$$

6. **Objective Computation**:
   - Calculate the objective function $J(t)$ as:

   $$J(t) = \frac{1}{2} \left(O(t) - D(t) \right)^2$$

   where $D(t)$ is the desired output.

7. **Adjustment**:
   - If $J(t)$ is not minimized, adjust parameters λ and η and repeat from Step 2.

4 Conclusion

The Raynoid Synthetica model provides a novel approach to understanding and simulating organoid intelligence. Future work will involve empirical testing and refining the model based on observed behaviors.