Module: Information Acceleration and Observational Hierarchies

April 1, 2025

1 Introduction

This module extends our prior discussions by introducing acceleration in directed graphs as a model for information propagation. We examine the accumulation of information in a manner similar to viral spread, introduce a moving observation window mechanism, and relate hierarchical observations to training in neural networks.

2 Information Spread as Viral Propagation

Let $G = (V, E)$ be a directed graph representing an information network, where V denotes nodes (information states) and E denotes directed edges (information transfer). Define the strength of information at a node v_i as a function $S(v_i)$ based on incoming information:

$$S(v_i) = \sum_{v_j \in \text{in-neighbors}(v_i)} w_{ji} S(v_j) \tag{1}$$

where w_{ji} is a weight function representing the influence of node v_j on v_i.

Consider a layered propagation model where the depth of nodes from an initial node v_0 is defined as levels L_k. The probability of information reaching level L_n is proportional to the aggregated strength along paths:

$$P(L_n) \propto \sum_{p \in \mathcal{P}_{0 \to n}} \prod_{(v_i, v_j) \in p} w_{ij} \tag{2}$$

where $\mathcal{P}_{0 \to n}$ represents all paths from v_0 to level L_n.

3 Moving Window Encoding and Memory Optimization

Define a moving observation window W_t over an information trajectory. Let W_t maintain a record of recent nodes and encode previous states with a compression function C. The update rule follows:

$$W_{t+1} = \begin{cases} \{v_{t+1}\} \cup W_t, & \text{if } |W_t| < k \\ \{v_{t+1}\} \cup C(W_t), & \text{otherwise} \end{cases} \tag{3}$$

where k is the memory threshold, and $C(W_t)$ compresses past nodes based on redundancy and relevance.

A mathematical rule for dropping information is defined using an entropy threshold H_T:

$$H(W_t) = -\sum_{v_i \in W_t} P(v_i) \log P(v_i) \tag{4}$$

where $P(v_i)$ is the frequency-based probability of encountering v_i. If $H(W_t) < H_T$, older nodes are removed.

4 Acceleration in Information Race

Define the acceleration of information propagation between levels as:

$$a_n = \frac{S(L_n) - S(L_{n-1})}{\Delta t} \tag{5}$$

where $S(L_n)$ is the cumulative information strength at level L_n and Δt is the time step. The most influential paths maximize acceleration, defining an optimal information trajectory.

5 Observation as Training

Observations are defined as changes in system state due to incoming signals. Define an observation function O as:

$$O : X \times I \to X' \tag{6}$$

where X is the state space, I is an input signal, and X' is the updated state. Hierarchical observations align with layers in neural networks, where each layer L_k abstracts features from the previous layer:

$$L_k = f_k(L_{k-1}) \tag{7}$$

where f_k represents a transformation function.

6 Conclusion

This module formalizes information acceleration, hierarchical observations, and moving window optimization in information networks. These principles will be integrated into the next iteration of our main research document.